Essays on intangible capital and economic development

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A thesis submitted to for the degree of Doctor of Philosophy of

The Australian National University.

Canberra, March 2018.

Declaration

I certify that the thesis I have presented for examination for the PhD degree of The Australian National University is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Chapter 1 was co-authored with Yixiao Zhou, and I contributed 80% of the work;

Chapter 2 was co-authored with Yixiao Zhou and Ligang Song, and I contributed 70% of the work;

Chapter 4 was co-authored with Xunpeng Shi, and I contributed 80% of the work;

Chapter 5 was co-authored with Creina Day, and I contributed 80% of the work.

Acknowledgement

I am in debt to a number of people for their insights, support and encouragement while completing my PhD program. Most importantly, I wish to thank Professor Ligang Song, Professor Kaliappa Kalirajan, Dr Creina Day and Dr Ying Xu for their invaluable advice and trust.

I would like to thank my co-authors Dr Yixiao Zhou and Dr Xunpeng Shi for their contributions to my thesis as well as my colleagues and peers at Crawford School and beyond for their helpful comments and fruitful discussions. I would also like to thank Karin Hosking for copyediting the thesis.

Finally, I would like to thank Rio-Tinto very much for funding my PhD study through the Rio Tinto-ANU China Partnership.

Abstract

This thesis consists of six chapters that examine issues on intangible capital and economic development. Chapter 1 assesses the role of intangible capital in sectoral economic growth in China based on data from Input-Output Tables, and identifies the type of disaggregated intangible capital that has the largest effect on economic growth in each sector group. Chapter 2 studies the determinants of intangible investment in Chinese firms as well as the relationship between firm-level productivity and various types of intangible investment, and finds that firm size, human capital and institutional quality as well as market competition all play important roles in determining firms' intangible investment. Chapter 3 investigates the role of organization capital in the production of Chinese listed firms, compares the contributions of organization capital to firms' financial performance between listed state-owned enterprises (SOEs) and non-SOEs and finds that SOEs invest more in organization capital but have lower returns from the investment. Chapter 4 analyses the effect of intangible capital in reducing sectoral energy intensity as well as how this effect varies across sectors and economies of different development stages, which provides some useful policy implications. Chapter 5 compares the changing output elasticity as well as heterogeneity in the productivity spillover effect of intangible capital across various sectors and economy of different income level, and finds some interesting patterns. Chapter 6, which is the last chapter, revisits the lost decades of the Japanese economy based on an extended neoclassical growth model with intangible investment incorporated and finds that unmeasured intangible investment actually plays an important role in explaining the business cycles during the Japanese lost decades.

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Introduction

'Why are some nations rich and others poor?', this is the big question that has bothered economists for decades. The most obvious answer is differences in labour productivity. In the past, we thought it was physical capital that led to the differences in labour productivity. However, in recent decades, some nations, some industries and some firms do not have a high amount of physical capital but they do demonstrate a high level of labour productivity. The first thought that comes to our mind is that it might be due to intangible capital, and the newest national account system (SNA08) as well as firm accounting standard have already captured some parts of it. However, due to the conservative nature of the national account and firm accounting standard, there is still a significant amount of intangible investment that remains unmeasured. Specifically, the firm accounting standard normally only capitalizes development costs that lead to measurable economic value. For research costs that improve knowledge and efficiency of firms but the economic value of which cannot be measured accurately, the firm accounting standard directly treats them as expenses. Although the new national account system SNA08 begins to capitalize R&D costs, other intangible capital such as organization capital, brand equity and staff training that significantly contributes to the value of firms has not been considered as capital. Moreover, there are still many developing economies that have not yet adopted SNA08, which means that their national account data excludes R&D expenditure as measured GDP. Therefore, a comprehensive system for measuring intangible capital, and relevant measurement technique are needed. Corrado et al. (2009) propose such a system, and they find that as much as 800 billion USD of intangible investment has been excluded from published US data (as in 2003).

There is a growing amount of literature based on or relevant to the study by Corrado et al. (2009), which can be divided into several streams. First, the measurement of intangible investment and its contributions to economic growth. For example, at national level, Fukao et al. (2009), van Ark et al. (2009), Corrado and Hulten (2010), Hulten and Hao (2012), and Chun and Nadiri (2016) have discussed the measurement of intangible investment and its contributions to economic development in Japan, Europe, the US, China and Korea respeciviely; at sectoral level, Corrado et al. (2014) and Chun and Nadiri (2016) provide data on intangible capital for various sectors across certain developed economies. Second, discussion of the role of intangible capital in firms' valuation and performance, such as organization capital (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013; Tronconi and Marzetti, 2011) and customer capital (Gourio and Rudanko, 2014a). Third, adding intangible capital to solve some macroeconomic issues. For instance, McGrattan and Prescott (2010) explain why the basic real business cycle model fails to explain the fluctuations of the US economy during the 1990s and early 2000s by revealing that unmeasured intangible investment grew much more than that of measured output and therefore measured productivity during the research period was underestimated; Goodridge et al. (2013) argue that inconsistent movement between hours growth and output growth in the UK after the Global Financial Crisis is because unmeasured intangible investment led to underestimated productivity growth; Gourio and Rudanko (2014b) demonstrates in their preliminary study that intangible investment can partially explain the movement of the labour wedge in business cycles.

Although many aspects of intangible capital have been well studied, there are still some important questions yet to be answered. For example, although unique features in developing economies such as underdeveloped institutions may interact with intangible capital, the role of intangible capital in developing economies has not been well documented due to the lack of data. Moreover, intangible capital as a production factor is changing the production structure of various sectors across the world and thus may impact the energy efficiency of those sectors, but relevant studies on the relationship between intangible capital and sectoral energy intensity as well as the heterogeneity of this relationship are rare. Furthermore, while intangible capital as a source of growth as well as its productivity spillover has been confirmed, the heterogeneity in its output elasticity and productivity spillover effect across sectors and economies has not received much attention. Finally, although some new macroeconomics theories with intangible capital incorporated have been proposed, they have rarely been tested widely. This thesis aims to fill the above gaps in the literature on intangible capital.

The first three chapters of this thesis focus on intangible capital in China. Chapter 1 assesses the role of various intangible capital in sectoral productivity and sectoral economic growth in China. By taking advantage of China's Input-Output Tables, a dataset of intangible capital for 100 sectors from 1997 to 2012 is constructed. Detailed analyses are conducted for aggregate intangible capital as well as its disaggregated components including computerized information, innovative property and economic competency across four sector groups (agriculture, light industry, heavy industry as well as service). It is found that growth in intangible capital explains almost 20% of the total factor productivity (TFP) growth over the period 1997 to 2012. At the sector level, it is revealed that different types of intangible capital play different roles across the four sector groups. Chapter 2 analyses the determinants and impacts of intangible investment in China using a firm-level dataset extracted from the World Bank China Enterprise Survey 2012. It is discovered that more human capital, larger firm size and better institutional quality generally increase the propensity and the amount of intangible investment, and yet fiercer market competition generally decreases both the propensity and the amount to invest in intangibles. The disaggregated components of intangibles are found to be positively correlated with firm productivity, and there is complementarity between software investment and organization investment. Chapter 3 studies the interaction between organization capital and firm human management practice using data from Chinese listed firms. Organization capital, unlike physical capital, is likely to be influenced by the human management practice of a firm. The listed firms of China provide a valuable sample for studying the interaction between human management practice and the efficiency of organization capital given that there exists a large number of listed state-owned enterprises (SOEs). The study finds that organization capital is indeed an important production factor in Chinese listed firms, and SOEs invest more in organization capital due to low employee' turnover but have a lower efficiency in organization capital compared with private enterprises.

The other three chapters include issues on intangible capital related to energy intensity, macroeconomics and productivity. Chapter 4 investigates the relationship between intangible capital and sectoral energy intensity and its heterogeneity across sectors and economies. Although intangible capital has been well documented to be essential for economic and productivity growth, relevant studies on its role in improving energy intensity are rare. This chapter establishes a relatively robust causal relationship between intangible capital and sectoral energy intensity, based on a rich dataset of 40 economies derived from the World Input-Output Database (WIOD) spanning across 13 years (1995 – 2007). The qualitative and quantitative interactions of this relationship with income level and sectoral heterogeneity are also revealed. Chapter 5 examines the heterogenous output elasticity and productivity spillover effect of intangible capital between sectors and economies. It is found that intangible capital significantly contributes to both output growth and productivity spillover, and both effects demonstrate an inverted U-shape relationship with income level and significantly vary across sectors. Chapter 6 surveys why the basic neoclassical growth model fails to explain the lost decades of the Japanese economy and demonstrates how the extension of intangible capital and non-neutral technology greatly improve the simulation results, which highlights the importance of intangible investment in Japanese business cycles.

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1. Intangible capital and China's economic growth: Evidence from Input-Output Tables*

This study uses data from Input-Output Tables and a methodology adopted from Corrado et al. (2009) to provide empirical evidence of the role of intangible capital in China by industrial sector. In doing so it offers a first and new methodology for measuring the role of intangible capital in a country where data on intangible capital are insufficient. It finds that growth in intangible capital explains almost 20% of the total factor productivity (TFP) growth over the period 1997 to 2012. Moreover, these effects of intangible capital remain robust under various forms of sensitivity analysis including bootstrap, Levinsohn and Petrin (2003) approach and changes in the depreciation rate. At the sector level, we find that research and development (R&D), which embodies innovation, plays a more important role in agriculture than economic competency and computerized information; but that the role of economic competency is more important than that of R&D and computerized information in the services and light industry sectors.

1.1 Introduction

China has enjoyed rapid growth since its reform and opening up policies were implemented in 1978. Real GDP per capita of China in 1978 was only one-fortieth of the US level and one tenth of the Brazilian level (Zhu, 2012). By 2015 however, China had real GDP per capita that was almost equal to one fourth of the US level and at the same level as Brazil[1]. Growth in total factor productivity (TFP) has played a critical role

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* This chapter is also published as a book chapter in *China Update 2017*.

[1] GDP per capita using PPP approach (constant 2011 international currency), data from International Comparison Program database, the World Bank.

in China’s growth miracle. According to Zhu (2012), positive change in TFP accounts for 78% of the growth in China’s GDP per capita between 1978 and 2007. The transition from the planned economy to the market economy is a major source of TFP growth and has significantly improved China’s TFP, but this source of TFP growth cannot last forever since return from earlier reforms is diminishing.

From the year 2012, Chinese economic growth has been slowing down and has entered a stage called the ‘New Normal’. The Chinese official definition of the ‘New Normal’ is that China will maintain stable and relatively lower growth compared with earlier growth rates. What could be the new source of growth of China in the stage of the ‘New Normal’? The script on the back of an iPhone may provide a hint. It reads, ‘Designed by Apple in California. Assembled in China.’ Payment to Chinese labour and profits of non-Apple companies respectively account for only 1.8% and 9.2% of the value added of an iPhone while profits of Apple takes up 58.5% of the total value added in 2010, according to Kraemer et al. (2011). This striking fact has an important implication: the distribution of value added in the global value chain is favourable to those who own the product design and hence the market power instead of those who manufacture the products.

Product design and market power embody a broader concept called intangibles (Corrado et al., 2009). Intangible capital consists of the stock of immaterial resources that enter the production process and are important for the creation or improvement of products as well as production processes (Arrighetti et al., 2014). In this study, intangible capital is defined in a broad way, following Corrado et al. (2009). Specifically, it includes innovative property (R&D), computerized information (software, database etc.) and economic competency (brand equity and organization capital). Intangible capital has been playing an increasingly important role in boosting productivity and economic growth since the ‘IT revolution’. In developed economies, the relative use of tangible capital is decreasing while the relative use of intangible capital, such as production technologies, product design, market power, and intangibles embodied in employees and firm structure, has been increasing (Chun and Nadiri, 2016; Corrado and Hulten, 2010; Fukao et al., 2009; Marrano et al., 2009; Miyagawa and Hisa, 2013; van Ark et al., 2009).

The literature on intangible capital is significant, and includes discussion of intangible capital as a source of growth in various countries at national level and industry level (Borgo et al., 2013; Chun and Nadiri, 2016; Corrado et al., 2013; Corrado and Hulten, 2010; Fukao et al., 2009; Haskel and Wallis, 2013; Marrano et al., 2009; Miyagawa and Hisa, 2013; van Ark et al., 2009), discussion of intangible capital in firms’ valuation and productivity (Arato and Yamada, 2012; Atkeson and Kehoe, 2005; Clausen and Hirth, 2016; Eisfeldt and Papanikolaou, 2014, 2013; Gourio and Rudanko, 2014a; Tronconi and Marzetti, 2011), and discussion of incorporating intangible capital to solve macroeconomic puzzles (Goodridge et al., 2013; Gourio and Rudanko, 2014b; McGrattan and Prescott, 2014, 2010). However, studies on intangible capital in China are scarce both due to the lack of data and the newer importance of intangible capital to the economy. Hulten and Hao (2012) calculate the intangible capital of China between

2000 and 2008 and conduct growth accounting of national data using the income share method. The authors gather only nine observations, which is not sufficient for a comprehensive analysis. Given China's shifting growth model and the possibility of utilizing alternative data sources, it is timely to further investigate the role of intangible capital in China's growth.

To the best of our knowledge, this study is the first empirical test of how intangibles enhance economic growth at sectoral level in China. In contrast to national-level study, industry-level study has the advantage of generating more observations and thus allows more statistical degrees of freedom to analyse how different categories of intangible capital impact on economic growth. This will provide a better way to assess the role of intangibles in an economy.

We divided one hundred sectors from China's Input-Output Tables of 1997, 2002, 2007 and 2012[2] into four subgroups: agriculture, light industry, heavy industry and service, to alleviate the problem of parameter heterogeneity between sectors. The selected Input-Output Tables are constructed using data from China's National Bureau of Statistics and Input-Output Survey. The measurement of intangible investment in this study follows the literature in capitalizing either intangible intermediates or intangible expenditure. Use of intermediates from input-output tables to estimate intangibles is common in previous literature[3], including Chun and Nadiri (2016), Corrado et al. (2014) and

[2] The reason we exclude the Input-Output Tables for 1987 and 1992 is that these two earlier tables are inaccurate and include few of the intangible intermediates.
[3] Intangible investment produced within firms is not reflected in input-output tables. However, as long as the ratio of actual intangible expenditure to the intangible expenditure manifested in the input-output

Miyagawa and Hisa (2013).

Different from Corrado et al. (2009), Fukao et al. (2009) and Hulten and Hao (2012), this study, however, uses a proxy approach. That is, using the entries relevant to intangible investment as proxies, and assuming that the ratios of intangible investments to the proxies remain constant over time. Using the proxy approach and assuming the ratio of true value to proxies constant overtime is also common in the literature on intangible capital. For example, Gourio and Rudanko (2014a) proxy the Selling & General Administration (S&GA) expense for investment in customer capital; Tronconi and Marzetti (2011) and Eisfeldt and Papanikolaou (2014) proxy S&GA expense for investment in organization capital. Although this assumption is often found to be invalid, it is the best this study could adopt based on the available data; if this assumption is true, the study will avoid the inaccurate measuring problems found in Corrado et al. (2009) and Fukao et al. (2009).

When conducting growth accounting, we adopt the Cobb-Douglas parameter estimation based on econometrics instead of income/cost shares, along the lines of Niebel et al. (2017). The advantage of this approach is to allow for the existence of error terms. The income share method used by Corrado et al. (2009), Fukao et al. (2009), and Hulten and Hao (2012) may, in contrast, underestimate the contribution of resource reallocation to economic growth when the economy is in disequilibrium, according to Nadiri (1970). In the case of a transitional economy like China, the economy is likely to remain in

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tables remains constant over time, the coefficients in the empirical analysis will not be biased.

disequilibrium over time. Therefore, the income share method is not suitable in the case of China. Our choice of econometric approach allows for an error term, which alleviates the problems arising from disequilibrium.

Our study also conducts bootstrap regressions to confirm the robustness of the results, which is new to the existing literature. Limited by the time span (T=4), the standard system GMM approach is not suitable for this study. Bootstrap is the only feasible method given data limitations. Studies on intangible capital often suffer from the problem of small samples. Bootstrap regressions alleviate this problem to some extent. Moreover, the depreciation rate of intangible capital is debatable. To confirm the significance of the impacts of intangible capital, we will conduct a sensitivity analysis by experimenting with various depreciation rates.

This study consists of five sections. In the next section, the methodology of growth accounting at the industry level is discussed, and a traditional growth accounting excluding intangible capital is conducted. Section 3 provides empirical evidence on the relationship between intangible capital and total factor productivity (TFP). In section 4, a growth accounting incorporating intangible capital is conducted. Section 5 draws the conclusion.

1.2 How do we conduct growth accounting with sectoral data?

Growth accounting often utilises the Cobb-Douglas production function:

$$Y = AK^{ak}L^{al},$$

where Y is GDP, A stands for the total factor productivity, and K represents the capital. If the object is a nation, then we directly take the logarithm of both sides and then run a regression. The parameters ak and al can be estimated in this way. However, with sectoral data, there is a problem: the parameters of each industry may vary. If a pooled regression is conducted, the heterogeneity of parameters will cause bias of the estimates. Moreover, each industry may have its own initial TFP value, which implies different intercepts of various industries. To cope with the problem of parameter heterogeneity, we categorize industries according to similarities in parameters following previous literature such as Harris and Robinson (2002). In this study, the subgroups are defined as follows: light industry, heavy industry, agriculture and service[4]. Then, we assume a Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{ak} L_{it}^{al} \tag{1}$$

Y_{it} is the value added of sector i at time t; A_{it} is the TFP of sector i at time t; K_{it} is the capital by traditional definition (excluding most of the intangibles); L_{it} is the number of labour input. ak and al are the capital and labour elasticities of output respectively. Due to sectoral heterogeneity, the initial values of TFP may be different across sectors. We therefore assume:

$$\mathrm{A}_{it} = \mathrm{A}_{i0} e^{\gamma t}$$

Take the logarithm of both sides:

$$\ln \mathrm{Y}_{it} = \ln \mathrm{A}_{it} + ak \ln \mathrm{K}_{it} + al \ln \mathrm{L}_{it} \tag{2}$$

The equation can be estimated by either the fixed effects model or the random effects model, depending on whether A_{i0} varies from sector to sector within a subgroup.

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4 The list of subgroups is demonstrated in Appendix A.

A key issue in production function estimation is, however, correlation between the un-observable productivity shocks and input levels. An industry responds to positive productivity shocks by expanding output and input. Negative shocks lead an industry to reduce output and input usage. When true, ordinary least square (OLS) estimates of production functions are likely to be biased, which leads to biased estimates of productivity. Olley and Pakes (1996) (OP) develop an estimation approach using investment as a proxy for these un-observable shocks. More recently, Levinsohn and Petrin (2003) (LP) point out that investment is lumpy. If this is true, then the investment proxy may not smoothly respond to productivity shocks. Levinsohn and Petrin (2003) suggest that using intermediate input can solve this problem. Therefore, here we also adopt growth accounting without intangibles[5] using the LP approach. The proxy used in this study is the usage of electricity, heating, fuel and water intermediates at 1997 constant prices[6].

The growth rate of TFP is backed out as:

$$g\_tfp = g_y - akg_k - alg_l \tag{3}$$

Capital and labour inputs are not available at a sectoral level as detailed as the one in China's Input-Output Tables. Luckily, China's Input-Output Tables have two variables: the total wages of labour and the depreciation of capital. We adjust the nominated

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[5] The LP approach allows only one capital variable. However, when incorporating intangible capital, there are at least two capital variables. Therefore, we do not conduct growth accounting with intangible capital using the LP approach.

[6] Deflators are obtained from National Bureau of Statistics of China and the World Input Output Database (WIOD).

depreciation of capital to real depreciation using the Price Index of Investment in Fixed Assets from National Bureau of Statistics of China.

Assume a constant depreciation rate θ as is the convention in previous literature:

$$\theta K_{it} = \text{real depreciation}_{it} \tag{4}$$

Then, it is clear that $\text{real depreciation}_{it}$ has a strictly linear relationship with K_{it} and therefore is a perfect proxy for capital. As for the quantity of labour, we have:

$$L_{it} = \frac{\text{total wage}_{it}}{\text{average wage}_{it}} \tag{5}$$

Total wage_{it} is from China's Input-Output Tables and average wage_{it} is from the Labour Statistics Yearbook of China. However, the sectoral classification in the Labour Statistics Yearbook of China is not as detailed as that in China's Input-Output Tables. Therefore, the average wage of the upper level of classification is used as a proxy for the average wage of individual sectors[7].

Substitute K_{it} in (2) with (4),

$$\ln Y_{it} = \ln A_{it} - ak\ln(\theta) + ak\ln \text{Capital\_proxy}_{it} + al\ln L_{it} \tag{6}$$

It is clear that substituting the capital proxy ($\text{real depreciation}_{it}$) for K_{it} is appropriate because the coefficient of $\text{real depreciation}_{it}$ is the same as that of K_{it}. The depreciation rate θ becomes a part of the intercept. The growth rate of K_{it} that is used for the calculation of TFP is exactly the same as the growth rate of $\text{real depreciation}_{it}$.

Table 1 reports the descriptive statistics of the variables used in regressions, over the

[7] The proxy is based on an assumption that the ratio of the average wage of a lower level sector to that of its upper level sector remains constant over time. If this assumption holds, then the constant ratio becomes a part of intercept similar to equation (6). Then the coefficient of the proxy is the same as the true coefficient.

period 1998 to 2012. It is clear that the ranges of value added, capital proxy, labour and different categories of intangible capital are large. This sample consists of 100 sectors in China across four years and therefore has nearly 400 observations.

Table 1 Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
ln(Value added)	overall	15.83	1.21	12.29	19.21	N =400
	between		1.07	13.10	18.55	n =100
	within		0.59	12.31	17.94	T =4
ln(Capital proxy)	overall	13.99	1.30	9.71	18.86	N =398
	between		1.08	11.35	17.57	n =100
	within		0.75	9.92	16.87	T-bar =3.98
ln(Labour)	overall	5.39	1.27	1.06	9.72	N =398
	between		1.22	1.33	9.63	n =100
	within		0.38	1.71	6.88	T-bar =3.98
ln(Intangible capital)	overall	13.22	1.85	8.58	17.79	N =398
	between		1.20	10.57	15.84	n =100
	within		1.41	10.20	16.97	T-bar =3.98
ln(R&D capital)	overall	10.22	2.38	2.67	15.65	N =394
	between		1.68	3.76	13.37	n =99
	within		1.70	6.57	13.48	T-bar =3.98
ln(EC capital)	overall	12.93	1.82	8.46	17.65	N =398
	between		1.18	10.24	15.56	n =100
	within		1.38	9.82	16.74	T-bar =3.98
ln(CI capital)	overall	9.94	2.26	1.07	15.55	N =397
	between		1.86	3.59	14.25	n =100
	within		1.29	5.86	13.24	T-bar =3.97

Notes: EC stands for economic competency and CI stands for computerized information.
Source: Authors' own calculation.

The results for growth accounting are displayed in Table 2. According to Hausman tests (please see Appendix C), random effects models are appropriate to study agriculture and light industry sectors, and fixed effects models are used for the heavy industry and services sectors. Both labour and depreciation are highly economically and statistically significant, and remain robust when using bootstrap regressions. A 1% change in capital stock is associated with 0.42%, 0.67%, 0.70% and 0.64% changes in value added in agriculture, heavy industry, light industry and service respectively. A 1% change in labour is associated with 0.57%, 0.26%, 0.13% and 0.22% changes in value added in agriculture, heavy industry, light industry and service respectively. The growth rate of TFP is calculated according to equation (3).

Table 2 Regression results for growth accounting without intangibles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Agriculture			Heavy industry			Light industry			Service		
VARIABLES	RE	RE bootstrap	LP	RE	RE bootstrap	LP	FE	FE bootstrap	LP	FE	FE bootstrap	LP
ln(Capital)	0.42***	0.42***	0.62***	0.67***	0.67***	0.39**	0.70***	0.70***	0.60***	0.64***	0.64***	0.42**
	(0.14)	(0.14)	(0.18)	(0.08)	(0.07)	(0.17)	(0.03)	(0.03)	(0.06)	(0.05)	(0.05)	(0.19)
ln(Labour)	0.57***	0.57***	0.34**	0.26**	0.26*	0.30***	0.13**	0.13**	0.29***	0.22**	0.22**	0.44***
	(0.0979)	(0.133)	(0.133)	(0.123)	(0.147)	(0.116)	(0.0577)	(0.0577)	(0.0505)	(0.0796)	(0.0989)	(0.0585)
Constant	6.48***	6.48***		4.99***	4.99***		5.37***	5.37***		5.60***	5.60***	
	(1.27)	(1.11)		(0.87)	(0.65)		(0.50)	(0.50)		(0.48)	(0.62)	
Observations	20	20	20	138	138	138	144	144	144	96	96	96
R-squared	0.79	0.79		0.81	0.81		0.88	0.88		0.86	0.86	
Number of id	5	5		35	35		36	36		24	24	

Notes: Cluster robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Number of bootstrap replications: 400 for normal bootstrap, 250 for LP.
Source: Authors' own calculation.

1.3 Intangible capital and TFP growth

According to Corrado et al. (2009), intangible investment consists of computerized information, innovative property and economic competency. Traditionally, intangible investment is classified as intermediate or expenditure and is therefore not manifested in national accounts. However, investment is the action of sacrificing today's consumption for increasing consumption in the future, according to Hulten (1979) and Corrado et al. (2009). Moreover, the effects of the intangible expenditure mentioned above last more than one year and therefore those expenses should be capitalized.

We follow the literature to measure intangibles by capitalizing intangible intermediates or intangible expenditure. Specifically, this study obtains relevant intermediate data from China's Input-Output Tables and assumes the ratio of the intermediate to the true intangible investment remains constant over time. The proxy approach is commonly adopted in measuring intangible investment and is well founded. For example, Gourio & Rudanko (2014) proxy the Selling & General Administration (S&GA) expense for customer capital investment; and Tronconi & Marzetti (2011) and Eisfeldt & Papanikolaou (2014) proxy S&GA expense for organization capital investment. Table 3 presents our proxies for intangible investment.

Table 3 Categories of intangible investment

	Proxy	**Comments**
1.Computerized information (mainly software)	Computer services and software intermediate	Include software
2.Innovative property		
(a)Scientific R&D	Research industry intermediate	Include R&D expenditure
(b)Non-scientific R&D		
3.Economic competencies		
(a)Brand equity (mainly advertising)	Culture, arts, radio, movie and television industry intermediate	Include parts of advertising expenditure
(b)Firm-specific resources (Organization capital and staff training)	Business service industry intermediate	Include advertising expenditure and organization investment
	Education industry intermediate	Include staff training

Notes: The intangible investment classification follows Corrado et al. (2009).
Source: Authors' own construction.

Following Corrado et al. (2009), intangible investment is deflated to 1997 constant price using the GDP deflator[8]. Since the interval of each Input-Output Table is five years, we

[8] The GDP deflator is obtained from the World Bank.

interpolate the missing data within the interval by assuming the growth rate is constant within the five-year interval. The depreciation rate of the intangible capital is set according to Corrado et al. (2009): 20% for R&D, 33% for computerized information, 60% for brand equity, and 40% for firm-specific resources. Based on these, we assume 40% for overall intangible and 50% for economic competency intangible. Intangible capital in 1997 was set to zero, and therefore 1998 is the first year for which this study calculates the intangible capital. According to Corrado et al. (2009), the year that initial capital stocks are zero has little effect on growth accounting analysis because depreciation rates are high and much previous capital has been depreciated away by the date we start the analysis, i.e., the year 1998. Moreover, the amount of intangible capital in China was considerably smaller in the 1990s, as manifested by low R&D (0.57% of GDP in 1996[9] and unavailable before 1996) and software use. Therefore, setting intangible capital in 1997 to zero will not cause significant problems.

Table 4 shows the trend of the sectoral average ratio of intangible to tangible. The amount of tangible capital is derived based on an assumed depreciation rate of 5%[10]. The amount of intangible capital is calculated using the method explained above. Accompanying China's rapid economic growth over the last two decades is a significant rise in its intangible-tangible ratio. However, compared with more advanced economies, the intensity of using intangible capital in China's production is still low and therefore there is great room for catch-up in the future. For example, the intangible-tangible ratios

[9] Data obtained from the World Bank.
[10] 5% is the most commonly used depreciation rate for the Chinese economy.

of Japan, the US, the UK in 2007 were 17%, 22% and 24%[11] respectively. Please note that parts of the proxies include expenditures that are not intangible investment and exclude those that are produced within firms. This suggests that the actual intangible-tangible ratio might be lower or higher than the figures in Table 4.

Table 4 Increasing trend of intangibles in China

	1998	2002	2007	2012
Sectoral average intangibles	1,573,790	8,880,930	24,017,800	59,924,580
Sectoral average tangibles	216,289,200	333,212,600	697,231,200	1280,413,600
Ratio	0.7%	2.7%	3.4%	4.7%

Unit: thousand RMB

Source: Authors' own calculation. Raw data obtained from China's Input-Output Tables.

Since TFP is the portion of output that cannot be accounted for by input (Comin, 2006), we should be careful when linking TFP to intangible capital. Change in TFP is possibly caused by changes in human capital and institutional quality. Changes in human capital and institutions are often not sector-specific, which can be controlled for at the national level. To capture human capital and institutional quality changes, this study uses two proxies. The first is GDP per capita and the second is time dummy that captures time effects. The positive correlation between economic development, human capital and institutional quality has been well documented (Weede et al., 2002; Gwartney et al., 2004), which forms the basis of using GDP per capita as the proxy for human capital and institutional quality. The time dummy provides a different overall TFP growth rate for each year so we can separate TFP growth at the national level from that caused by changes in intangible capital within individual industries. To control for the scale of an industry, the indicator of intangible capital is the ratio of intangibles to tangibles instead

[11] Tangible capital data is obtained from the Penn World Table 8.1 and intangible capita data is obtained from the cross-country intangible investment data website (http://www.intan-invest.net/).

of the absolute amount of intangibles. Table 5 demonstrates the relationship between the growth rate of TFP and the growth rate of the intangible to tangible ratio. Please note that there are two types of total factor productivity: one is TFP derived from RE/ FE models and the other is TFP, LP derived from the LP models, which are used to check the robustness of our results.

Table 5 Relationship between intangible-tangible ratio and growth of TFP

	$\Delta\ln(\mathrm{TFP})$						$\Delta\ln(\mathrm{TFP, LP})$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
$\Delta\ln(\mathrm{Intangible/tangible})$	0.20***	0.20***	0.25***	0.20***	0.20***	0.25***	0.14***	0.14***	0.16***	0.14***	0.14***	0.16***
	(0.05)	(0.07)	(0.08)	(0.05)	(0.07)	(0.08)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
$\Delta\ln(\mathrm{GDP\ per\ capita})$	0.42***	0.42**	0.56***				0.30**	0.30**	0.39***			
	(0.16)	(0.17)	(0.20)				(0.13)	(0.13)	(0.14)			
Constant	-0.33***	-0.33**	-0.45***	-0.16**	-0.16*	-0.23**	-0.12	-0.12	-0.19*	0.02	0.02	-0.02
	(0.12)	(0.14)	(0.17)	(0.07)	(0.09)	(0.11)	(0.09)	(0.10)	(0.11)	(0.05)	(0.06)	(0.07)
Observations	298	298	298	298	298	298	298	298	298	298	298	298
R-squared	0.18	0.18	0.23	0.27	0.27	0.32	0.11	0.11	0.15	0.25	0.25	0.30
Year FE	NO	NO	NO	YES	YES	YES	NO	NO	NO	YES	YES	YES
Number of id		100	100		100	100		100	100		100	100

Notes: cluster robust standard errors in parentheses except OLS, OLS is with robust standard error. *** p<0.01, ** p<0.05, * p<0.1. Number of bootstrap replications: 400 for normal bootstrap, 250 for LP. TFP denotes the total factor productivity derived from RE/FE models while TFP, LP denotes the total factor productivity derived from LP models.

Source: Authors' own calculation.

Importantly, the growth rate of the intangible-tangible ratio is economically and statistically significant across all specifications. A 1% growth in the intangible tangible ratio is associated with 0.26%, 0.26%, 0.31%, 0.26%, 0.26%, 0.31% growth in TFP respectively according to models (1) – (6). A 1% growth in the intangible-tangible ratio is associated with a 0.14%, 0.14%, 0.16%, 0.14%, 0.14%, 0.16% growth in TFP, LP respectively according to models (7) – (12). Growth of the intangible tangible ratio also explains a significant amount of TFP change, respectively at 17% according to model (4) and at 11% according to model (10)[12]. The significant impact of intangibles on TFP is consistent with the findings of Corrado et al. (2014). Corrado et al. (2014) regress TFP on intangibles, ICT and other variables and find that intangible capital is the only one that is significant. With GDP per capita and time effects as the control variables and the fixed effects estimator, the intangible to tangible ratio is still statistically and economically significant, which suggests that the finding is robust. Based on the above evidence, we thus conclude that intangible capital does play a significant role in China's productivity increase.

Another interesting question to ask is how the contributions of different categories of intangible capital to TFP growth differ. Table 6 shows the results of the effects of different intangible capital on TFP growth. When using TFP derived from RE/ FE models, all categories of intangible capital play important roles in the growth of TFP, being robust across all the models. Specifically, according to model (4), a 1% increase

[12] The square of partial correlation coefficient between $\Delta\ln(\mathrm{TFP})/\Delta\ln(\mathrm{TFP,LP})$ and $\Delta\ln(\mathrm{Intangible/tangible})$ is the percentage of variance in $\Delta\ln(\mathrm{TFP})/\Delta\ln(\mathrm{TFP,LP})$ that can be explained by $\Delta\ln(\mathrm{Intangible/tangible})$ in a model specification. Therefore, the 17% and 11% here are the squares of partial correlation coefficients between the two variables of interest in model (4) and model (10).

in the ratio of computerized information capital to tangible capital is associated with 0.08% of growth in TFP; a 1% growth in the ratio of R&D capital to tangible capital is associated with 0.11% of growth in TFP; a 1% growth in the ratio of economic competency capital to tangible capital is associated with 0.13% of growth in TFP. This is consistent with Chun et al. (2012) who find that innovative property is the most significant among all sorts of intangible investments when they are used to explain the growth of TFP in the Japanese economy. However, when the method of deriving TFP changes from FE/RE models to LP models, the results differ. Although the scale of the coefficients has not changed dramatically, the statistical significance has. Computerized information capital is no longer significant, and economic competency is insignificant when year effects not controlled. R&D capital remains generally significant. When it comes to the scale of the effects, according to model (8), a 1% growth in the ratio of computerized information capital to tangible capital is associated with a 0.03% increase in TFP, LP; a 1% growth in the ratio of R&D capital to tangible capital is associated with a 0.04% increase in TFP, LP; a 1% growth in the ratio of economic competency capital to tangible capital is associated with a 0.11% increase in TFP, LP.

Table 6 Impact of growth of different categories of intangible-tangible ratio on growth of TFP

VARIABLES	Δln(TFP) (1) OLS	(2) RE	(3) OLS	(4) RE	Δln(TFP, LP) (5) OLS	(6) RE	(7) OLS	(8) RE
Δln(CI/Tangible)	0.07**	0.07**	0.06*	0.06*	0.05	0.05	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Δln(R&D/Tangible)	0.11***	0.11***	0.07**	0.07***	0.09***	0.09***	0.04	0.04*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Δln(EC/Tangible)	0.08*	0.08*	0.12***	0.12***	0.05	0.05	0.11***	0.11***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-0.05	-0.05	-0.14***	-0.14***	0.07*	0.07**	-0.05	-0.05
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	196	196	196	196	196	196	196	196
R-squared	0.30	0.30	0.35	0.35	0.21	0.21	0.31	0.31
Year FE	NO	NO	YES	YES	NO	NO	YES	YES
Number of id		98		98		98		98

Notes: cluster robust standard errors in parentheses except OLS, OLS is with robust standard error. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Cluster robust standard error is unavailable when using FE models due to insufficient rank and therefore FE models are not used. CI stands for computerized information (mainly software); R&D stands for innovative property; EC stands for economic competency. TFP denotes the total factor productivity derived from RE/FE models while TFP, LP denotes the total factor productivity derived from LP models.

Source: Authors' own calculation.

1.4 Growth accounting incorporating intangible capital

According to Corrado et al. (2009), the production function could be written as below when intangible capital is incorporated:

$$Y = AK^{ak}I^{ai}L^{al}$$

where *I* is the intangible capital stock and *ai* is the output elasticity of intangible capital. When intangible expenditure is viewed as investment, it should be counted as value added according to the national account identity (Corrado et al., 2009). Therefore, when conducting growth accounting with intangible capital, an even more accurate measurement of intangible investment is required. In this study, however, we do not know the ratio of true intangible investment to the proxies. One feasible action is to assume 100% as the base case[13].

Table 7 demonstrates the results of growth accounting incorporating intangible capital. The impacts of intangibles on economic growth of all the subgroups are economically and statistically significant. A 1% increase in intangible capital is respectively associated with 0.16%, 0.22%, 0.14% and 0.24% output growth in agriculture, heavy industry, light industry and service. This indicates that intangible capital has become an important source of growth in the Chinese economy.

Table 7 Results of growth accounting with intangibles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agriculture		Heavy industry		Light industry		Service	
VARIABLES	RE	RE bootstrap	RE	RE bootstrap	FE	FE bootstrap	FE	FE bootstrap
ln(Tangibles)	0.36***	0.36***	0.29***	0.29**	0.40***	0.40***	0.32***	0.32***
	(0.09)	(0.13)	(0.11)	(0.12)	(0.04)	(0.04)	(0.08)	(0.09)
ln(Labour)	0.54***	0.54***	0.44***	0.44***	0.37***	0.37***	0.39***	0.39***
	(0.04)	(0.09)	(0.11)	(0.10)	(0.06)	(0.06)	(0.07)	(0.10)
ln(Intangibles)	0.16***	0.15**	0.22***	0.22***	0.14***	0.14***	0.24***	0.24***
	(0.05)	(0.08)	(0.05)	(0.05)	(0.02)	(0.02)	(0.05)	(0.06)
Constant	5.68***	5.65***	6.56***	6.56***	6.36***	6.36***	6.09***	6.09***
	(0.38)	(0.54)	(0.74)	(0.83)	(0.39)	(0.39)	(0.49)	(0.68)
Observations	20	20	138	138	144	144	96	96
R-squared	0.87	0.87	0.88	0.88	0.92	0.92	0.93	0.93
Number of id	5	5	35	35	36	36	24	24

Notes: cluster robust standard errors in parentheses except OLS, OLS is with robust standard error.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' own calculation.

As mentioned earlier, intangible capital can be divided into computerized information, innovative property and economic competency. A question to be investigated is whether their roles differ across industries. To answer this question, we first assume a production

[13] The value of proportion does not matter for the results. When varying the proportion, the results remain similar. For details of how the proportion is changed, please see Appendix B.

function in which intangible capital is decomposed:

$$Y = AK^{ak}IC^{ai1}RD^{ai2}EC^{ai3}L^{al}$$

where CI stands for computerized information (mainly software); RD stands for innovative property (R&D); EC stands for economic competency; $ai1$, $ai2$ and $ai3$ are the output elasticities of the three inputs respectively.

Table 8 shows the results of growth accounting using the above production function. Not all categories of intangible capital are significant (e.g. economic competency within agricultural sector; R&D within services). One reason might be the strong positive correlation between different categories of intangible capital due to their co-movement. However, from the results in Table 8, we are able to obtain some information on the roles of different intangible capital in different industries. In agriculture, R&D is significant and positive. A 1% increase in R&D capital is predicted to increase a sector's value added by 0.15%. The coefficients of economic competency and computerized information are small, which may indicate that their effects are trivial. In heavy industry, all are economically and statistically significant. A 1% increase in R&D, economic competency and computerized information is associated with 0.13%, 0.11% and 0.04% growth in value added respectively. In light industry, both R&D and economic competency capital are significant. A 1% growth in R&D and economic competency is respectively correlated with 0.08% and 0.14% increases in value added. The coefficient of computerized information capital is insignificant and small. Therefore, economic competency capital is likely to play the most important role in China's light industry among the three categories of intangible capital. In services, only economic competency is significant. A 1% increase in economic competency capital is associated with 0.25% of value added growth. The coefficients of both R&D and computerized information capital are insignificant and small in value, which may imply that economic competency is the most important category of intangible capital in service.

Table 8 Results of growth accounting with detailed intangible capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agriculture		Heavy industry		Light industry		Service	
VARIABLES	RE	RE bootstrap	RE	RE bootstrap	FE	FE bootstrap	FE	FE bootstrap
ln(Tangibles)	0.35***	0.35	0.22***	0.22**	0.30***	0.30***	0.29***	0.29***
	(0.08)	(0.27)	(0.09	(0.10)	(0.06)	(0.05)	(0.06)	(0.07)
ln(Labour)	0.52***	0.52**	0.49***	0.49***	0.44***	0.44***	0.39***	0.39***
	(0.06)	(0.21)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.11)
ln(RD)	0.15***	0.15	0.13***	0.13***	0.08**	0.08**	0.02	0.02
	(0.03)	(0.15)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
ln(EC)	0.02	0.02	0.11***	0.11**	0.14***	0.14***	0.25***	0.25***
	(0.05)	(0.13)	(0.04)	(0.05)	(0.02)	(0.03)	(0.05)	(0.05)
Ln(CI)	-0.06***	-0.06	0.04**	0.04**	-0.01	-0.01	0.02	0.02
	(0.01)	(0.07)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)
Constant	6.57***	6.57***	7.02***	7.02***	6.78***	6.78***	6.05***	6.05***
	(0.81)	(1.70)	(0.60)	(0.79)	(0.39)	(0.43)	(0.41)	(0.67)
Observations	20	20	137	137	144	144	92	92
R-squared	0.99	0.99	0.93	0.93	0.94	0.94	0.94	0.94
Number of id	5	5	35	35	36	36	23	23

Notes: cluster robust standard errors in parentheses except OLS, OLS is with robust standard error. *** p<0.01, ** p<0.05, * p<0.1. CI stands for computerized information (mainly software); R&D stands for innovative property; EC stands for economic competency.

Source: Authors' own calculation.

1.5 Conclusion

Intangible capital and its various forms – technology, product design, marketing and organizational development – is the foundation of knowledge economies. According to our results, China, a transitional economy, has started to benefit from the rapid growth of intangible capital. Using China's Input-Output Tables of various years, this study provides an important insight into the role of intangible capital in different industries in the context of an emerging knowledge economy. It is specifically found that growth in intangible capital is significantly associated with TFP growth in China, and explains almost 20% of the TFP growth over the sample period. The results are generally robust across the different model specifications.

This study also reveals the relative importance of different categories of intangible capital in different industries. In agriculture, R&D is likely to play a critical role, but the role of other intangible capital is relatively trivial. To the heavy industry sector, R&D, computerized information (mainly software) and economic competency all are important to growth, but R&D is the most important. While the effects of both economic competency and R&D are significant to the growth of light industry, R&D is more significant. Last but not least, in service, the role of economic competency is critical while others are relatively unimportant. In other words, the role of R&D is important across all non-service industries while the role of economic competency is paramount across all non-agriculture industries.

The usage of intangible capital in production in China, however, remains relatively small compared with that in advanced economies. In 2007, the intangible-tangible ratio in China was approximately 3.4%. This compares to the same ratio for Japan, the US, the UK being 17%, 22% and 24% respectively. This is consistent with China's role at the assembly end of global value chains and the fact that the investment in design / intellectual property / brands remains the preserve of more developed economies. Given that the productivity boost from 'reform and opening up' is diminishing and China has entered the 'New Normal', it is evidently time for China to invest in new sources of growth – and clearly intangible capital is one of them.

The transformation from 'made in China' to 'designed in China' has a long way to run, but the shifts in the intangible to tangible ratio identified here suggest that China is catching up to frontier economies. Given the gradually increasing intangible capital in China, there is every reason to believe that rapid growth in intangible capital will become an increasingly important driver of China's economic growth.

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1.6 Appendix A Industry classification

	Name	Subgroup
1	Farming	Agriculture
2	Forestry	Agriculture
3	Livestock products	Agriculture
4	Fisheries	Agriculture
5	Agricultural services	Agriculture
6	Coal mining and processing	Heavy industry
7	Petroleum and natural gas extraction	Heavy industry
8	Ferrous metals mining and processing	Heavy industry
9	Non-ferrous metals mining and processing	Heavy industry
10	Non-metal minerals mining and processing	Heavy industry
11	Processing of petroleum and nuclear fuel	Heavy industry
12	Processing of coke	Heavy industry
13	Manufacture of chemical raw materials	Heavy industry
14	Manufacture of fertilizer	Heavy industry
15	Manufacture of pesticide	Heavy industry
16	Manufacture of organic chemical products	Heavy industry
17	Manufacture of rubber	Heavy industry
18	Manufacture of plastics	Heavy industry
19	Manufacture of cement and asbestos products	Heavy industry
20	Manufacture of non-metallic mineral products	Heavy industry
21	Iron steel products	Heavy industry
22	Smelting of steel	Heavy industry
23	Smelting of alloy iron	Heavy industry
24	Smelting of non-ferrous metals	Heavy industry
25	Processing of non-ferrous metals	Heavy industry
26	Manufacture of boiler, engines and turbine	Heavy industry
27	Manufacture of metalworking machines	Heavy industry
28	Manufacture of other general industrial machinery	Heavy industry
29	Manufacture of agriculture, forestry, animal husbandry and fishing machinery	Heavy industry
30	Manufacture of other special industrial equipment	Heavy industry
31	Manufacture of railway equipment	Heavy industry
32	Manufacture of automobiles	Heavy industry
33	Manufacture of ships equipment	Heavy industry
34	Manufacture of other transportation equipment	Heavy industry
35	Manufacture of generator	Heavy industry
36	Recycling and disposal of waste	Heavy industry
37	Production and distribution of electric power	Heavy industry
38	Production and distribution of gas	Heavy industry
39	Production and distribution of tap water	Heavy industry
40	Construction	Heavy industry

41	Crops, cooking oil and feed processing	Light industry
42	Manufacture of sugar	Light industry
43	Processing of meat	Light industry
44	Processing of aquatic products	Light industry
45	Processing of other food	Light industry
46	Manufacture of alcohol	Light industry
47	Manufacture of drinks and tea	Light industry
48	Manufacture of tobacco	Light industry
49	Manufacture of textiles from cotton	Light industry
50	Manufacture of textiles from wool	Light industry
51	Manufacture of textiles from fibre and silk	Light industry
52	Manufacture of knit products	Light industry
53	Manufacture of textile products	Light industry
54	Manufacture of textile, apparel, footwear, and caps	Light industry
55	Manufacture of leather, fur, feather and related products	Light industry
56	Processing of timber, manufacture of wood bamboo, rattan, palm and straw products	Light industry
57	Manufacture of paper and paper products	Light industry
58	Printing and recorded media	Light industry
59	Manufacture of articles for culture, education and sport activity	Light industry
60	Manufacture of chemical products for daily use	Light industry
61	Manufacture of other chemical products	Light industry
62	Manufacture of medicines	Light industry
63	Manufacture of chemical fibres	Light industry
64	Manufacture of glass and glass products	Light industry
65	Manufacture of pottery, china and earthenware	Light industry
66	Manufacture of fireproof products	Light industry
67	Manufacture of metal products	Light industry
68	Manufacture of household electric appliances	Light industry
69	Manufacture of other electric machinery and equipment	Light industry
70	Manufacture of computers	Light industry
71	Manufacture of communication and other electronic equipment	Light industry
72	Manufacture of other household electronic appliances	Light industry
73	Manufacture of electronic element and devices	Light industry
74	Manufacture of measuring instruments	Light industry
75	Manufacture of articles equipment for culture, education and sport activity	Light industry
76	Manufacture of artwork and other manufacturing	Light industry
77	Railway transport	Service
78	Road transport	Service
79	Pipeline transport	Service
80	Air transport	Service
81	Water transport	Service

82	Storage	Service
83	Postal services	Service
84	Telecommunications	Service
85	Catering	Service
86	Finance	Service
87	Insurance	Service
88	Real estate	Service
89	Accommodation	Service
90	Resident services and other services	Service
91	Entertainment	Service
92	Polytechnic services	Service
93	Health care	Service
94	Education	Service
95	Sports	Service
96	Social welfare	Service
97	Culture, arts, Radio and television	Service
98	Research and experimental development	Service
99	Geological prospecting	Service
100	Public administration and social organization	Service

1.7 Appendix B Sensitivity analysis

The depreciation rate of intangible capital is often not well grounded, both in this study and previous studies. To check the robustness of the results, a sensitivity analysis is conducted. The changes in parameters in this study are comprehensive and in two directions: either increase or decrease. If the changes in both directions make little difference, then the contributions of the intangible capital to economic growth are believed to be robust.

Table B1 Changes of parameters in sensitivity analysis

	Base	**Case**									
	case	1	2	3	4	5	6	7	8	9	10
Proxy ratio	100%	50%	150%								
δ(Intangible)	40%			60%	20%						
δ(RD)	20%					10%	40%				
δ(EC)	50%							25%	75%		
δ(CI)	33%									11%	66%

Notes: Proxy ratio refers to the ratio of the actual intangible investment to the proxy; δ refers to the depreciation rate; RD stands for R&D capital; EC stands for economic competency capital; CI refers to computerized information capital (mainly software).
Source: Author's own construction.

All the sensitivity analysis results are available upon contacting the author. The changes in parameters do not change the significance and signs of the intangibles and the changes in regression coefficient is only slight. Therefore, the impacts of intangible capital on productivity are considerably robust.

1.8 Appendix C Hausman test for Table

Table C1 Hausman test for various sectors

Ho: difference in coefficients not systematic

Sector	Agriculture	Light industry	Heavy industry	Service
Prob>chi2	0.2897	0.4841	0.0122	0.0769

2. Determinants of intangible investment and its impacts on firms' productivity: Evidence from Chinese private manufacturing firms*

Using data from the China Enterprise Survey 2012 conducted by the World Bank, this study examines the determinants of intangible investment and its impacts on firms' productivity by private manufacturing firms in China, thus shedding light on recent development of intangibles in one of the largest emerging economies in the world. It is found that more human capital, larger firm size and better institutional quality increase the propensity and amount of intangible investment, and yet fiercer market competition generally decreases both the propensity and the amount to invest in intangibles. We also provide evidence that the disaggregated components of intangibles are positively correlated with firm productivity and there is complementarity between software investment and organization investment. Implications for policies to enhance investment in intangibles are identified from the empirical results.

2.1 Introduction

Intangible capital consists of the stock of immaterial resources that enter the production process and are important for the creation or improvement of products as well as production process (Arrighetti et al., 2014). Examples of intangible capital include research and development (R&D) investment, advertising, organization capital, staff training, technology licences, patents, and copyrights (Corrado et al., 2013). It has been

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* This chapter is also published in *China and World Economy*.

identified in the existing literature that intangible capital is playing a growing role in determining firm productivity and thus the performance of local economies (Marrocu et al., 2012). These mechanisms are at play especially strongly in developed economies where competition is mainly based on ideas and innovation and hence firms are incentivized to invest resources in developing intangibles. Corrado et al. (2009) estimate that the total value of intangible capital in the United States was approximately $3.6 trillion by the early 2000s, suggesting that intangible investment accounted for over 10 to 20% of US output growth during that period. Similar phenomena are found in other countries including Japan, Korea, a number of OECD economies and China (Awano et al., 2010; Borgo et al., 2013; Chun and Nadiri, 2016; Corrado et al., 2013; Corrado and Hulten, 2010; Fukao et al., 2009; Haskel and Wallis, 2013; Li and Wu, 2017; Marrano et al., 2009; Miyagawa and Hisa, 2013; van Ark et al., 2009). Therefore, it is not surprising that recent literature has devoted increasing effort to defining and measuring intangible capital and studying its effects on productivity growth (Bontempi and Mairesse, 2007; Marrocu et al., 2012).

Apart from measuring intangible capital and its effects on productivity, the mechanisms that drive firms to invest in intangibles have increasingly received attention from researchers and policy makers (Ebner and Bocek, 2015; Hughes et al., 2006; OECD, 2011, 2010). Arrighetti et al. (2014) use data for Italian firms to examine the determinants of firms' investment in intangibles and reveal that a firm with a larger size, more human capital and more organizational complexity is more likely to invest in intangibles. However, studies on why firms invest in intangibles in emerging economies are scarce. Compared with developed economies, emerging economies are often regarded to be operating at the lower end of the global value chain, thus requiring relatively small intangible capital stock for production activities. Intangible capital often plays an important role in firms' profitability and competitiveness (Marrocu et al. 2012). In order to climb up the global value chain, however, firms in developing economies need to increase their intangible capital stock, which helps boost competitiveness of products as well as productivity of firms. Therefore, understanding the drivers underlying firms' investment in intangibles in an emerging economy provides useful information to policy makers who hope to support firms' investment in intangibles and enhance technological and industrial upgrading of the economy.

Another motivation that prompts us to examine intangible investment in an emerging economy is that the market environment of emerging economies is often different from that in developed economies. Emerging economies tend to have lower human capital and underdeveloped institutions. Moreover, because of the lack of core technology and patents, firms herein tend to be faced with intense competition on a cost-cutting basis. It is therefore important that we examine the determinants of firms' intangible investment in an emerging economy and reveal how the mechanisms may differ from those in developed economies.

China, one of the largest emerging economies in the world, shares many characteristics featured in other emerging economies. To be specific, China has relatively low human capital, underdeveloped institutions, and most of its products face a highly competitive market. China has relatively low intangible capital stock as well. The intangible tangible ratios[1] of Japan, the United States, and the United Kingdom are 17%, 22%, and 24%[2] respectively, while that of China was less than 4% in 2007[3]. Using cross-sectional firm-level data from the China Enterprise Survey 2012 conducted by the World Bank, this study identifies a theoretical framework underlying firms' intangible investment, tests the determinants of firms' intangible investment derived from the theoretical framework, and lastly examines the relationship between intangible investment and firm productivity.

To our best knowledge, this study is the first to examine the determinants of different types of intangible investment by Chinese firms and to provide a comprehensive analysis of how various components of intangible investment impact on firm-level productivity. In contrast to previous studies on developed economies such as Arrighetti et al. (2014), this study highlights the importance of institutional quality and market competition in the context of an emerging and developing economy, and reveals that both factors significantly affect the decision to invest in intangibles.

The paper is organized as follows: the next section provides a theoretical framework for analyzing the determinants of intangible investment by a firm. Section 3 describes data and the empirical strategy and provides summary statistics. Section 4 presents the pattern of intangibles investment in China. Section 5 presents the empirical results on

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[1] Intangible tangible ratio refers to the ratio of intangible capital to tangible capital.
[2] Tangible capital data is obtained from the Penn World Table 8.1 and intangible capital data is obtained from the cross-country intangible investment data website (http://www.intan-invest.net/).
[3] Unpublished manuscript of the authors of this paper.

the determinants of intangible investment and how this investment impacts on firm productivity. Section 6 draws the conclusion and policy implications from our findings.

2.2 Theoretical framework for analysing firms' behaviour in intangible investment

In this section, we develop a theoretical framework on firms' intangible investment and derive the hypotheses to be tested with firm-level data in the next section. Assume that a firm produces goods and services according to the following production function:

$$\mathrm{Y} = \mathrm{A}(\mathrm{IC}, \mathrm{H}, \theta)\mathrm{F}(\mathrm{L}, \mathrm{K})$$

where Y is value added produced by the firm; H is human capital; L is labour; K is physical capital; A is total factor productivity; IC is intangible capital; and θ represents other factors determining total factor productivity. F is a continuous function of L and K with $\mathrm{F}' > 0$ and $\mathrm{F}'' < 0$, which reflects diminishing marginal returns of labour and capital input. Total factor productivity A is an increasing function of intangible capital, human capital and other factors, which reflects the fact that intangible capital and human capital improve the efficiency and total factor productivity of a firm. The productivity boost from intangible capital and human capital follows diminishing marginal return. That is,

$$\frac{\partial \mathrm{A}}{\partial \mathrm{IC}} > 0,\ \frac{\partial^2 \mathrm{A}}{\partial^2 \mathrm{IC}} < 0,\ \frac{\partial \mathrm{A}}{\partial \mathrm{H}} > 0,\ \frac{\partial^2 \mathrm{A}}{\partial^2 \mathrm{H}} < 0 \text{ and } \frac{\partial \mathrm{A}}{\partial \mathrm{IC}\,\partial \mathrm{H}} = \frac{\partial \mathrm{A}}{\partial \mathrm{H}\,\partial \mathrm{IC}} > 0.$$

The quality of the human resources employed by firms is a key condition both for the generation of new intangible assets and the exploitation of existing intangible assets (Abramovitz and David, 2000; Galor and Moav, 2004). Given the fact that the production of intangible capital such as R&D and organization capital requires highskilled workers, increases in human capital lowers the costs of investing in new intangible capital as well as the cost of using existing intangible capital.

If a firm has sufficient funds, whether it invests in intangible capital or not depends on the relative marginal return of intangible capital compared with that of tangible capital[4].

The marginal return from investing in intangible capital is

$$\frac{\partial \mathrm{Y}}{\partial \mathrm{IC}} = \mathrm{F(L, K)} \frac{\partial \mathrm{A(IC, H, \theta)}}{\partial \mathrm{IC}}$$

The marginal return from investing in tangible capital is

$$\frac{\partial \mathrm{Y}}{\partial \mathrm{K}} = \mathrm{A(IC, H, \theta)} \mathrm{F}_K\mathrm{(L, K)}$$

Then the difference in marginal return between intangible and tangible capital (DMR) is

$$\mathrm{DMR} = \mathrm{F(L, K)} \frac{\partial \mathrm{A(IC,H,\theta)}}{\partial \mathrm{IC}} - \mathrm{A(IC, H, \theta)} \mathrm{F_K(L, K)} \quad (1)$$

Higher DMR indicates that a firm is more likely to invest in intangible capital instead of tangible capital.

From equation (1), we obtain

$$\frac{\partial \mathrm{DMR}}{\partial \mathrm{K}} = \mathrm{F_K(L, K)} \frac{\partial \mathrm{A(IC, H, \theta)}}{\partial \mathrm{IC}} - \mathrm{A(IC, H, \theta)} \mathrm{F_{KK}(L, K)} > 0^{5}$$

Intuitively, as the tangible capital of a firm increases, the marginal return of tangible capital falls. Meanwhile, as intangible capital improves productivity, that is $\frac{\partial \mathrm{A(IC,H,\theta)}}{\partial \mathrm{IC}} > 0$, return of an additional unit of intangible capital increases as the amount of tangible capital increases. Both of these two effects cause increased DMR as tangible capital grows. As a result, higher tangible capital leads to an increase in DMR, making it more likely that the firm invests in intangibles.

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[4] Tangible capital is also called physical capital.

[5] Noting that $\mathrm{F_{KK}(L, K)} < 0$ and $\mathrm{A(IC, H, \theta)} > 0$ and therefore $\mathrm{F_K(L, K)} \frac{\partial \mathrm{A(IC,H,\theta)}}{\partial \mathrm{IC}}$ and $-\mathrm{A(IC, H, \theta)} \mathrm{F_{KK}(L, K)}$ are both positive.

This mechanism is summarized as Hypothesis 1 below:

Hypothesis 1. A larger firm is more likely to invest in intangible capital, with firm size measured by the fixed assets (tangible capital) of the firm.

Besides firm size, human capital might also influence firms' decisions about intangible investment. Higher human capital lowers the costs of producing new intangible capital and improves the efficiency of using existing intangible capital and therefore raises the probability of investing in intangible capital. One example that reflects such complementarities between human capital and intangible capital is the large amount of human resources employed in direct R&D activities (Liu et al., 2000). More examples include the use of advanced software and the introduction of new management practices, which all need to be carried out by people with high levels of education.

With $\mathrm{F(L,K)} > \mathrm{F}_K\mathrm{(L,K)}$[6] and $\frac{\partial \mathrm{A}}{\partial \mathrm{IC}\,\partial \mathrm{H}} > \frac{\partial \mathrm{A}}{\partial \mathrm{H}}$[7], we obtain

$$\frac{\partial \mathrm{DMR}}{\partial \mathrm{H}} = \frac{\partial \mathrm{A}}{\partial \mathrm{IC}\,\partial \mathrm{H}}\mathrm{F(L,K)} - \frac{\partial \mathrm{A}}{\partial \mathrm{H}}\mathrm{F}_K\mathrm{(L,K)} > 0$$

which is summarized as Hypothesis 2 below:

Hypothesis 2. A firm with more human capital is more likely to invest in intangible capital.

Institutional quality is another important factor influencing the investment in intangible

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[6] This is often true in this context. Use the Cobb-Douglas form production function as an example: $\mathrm{F(L,K)} = \mathrm{L}^{\alpha}K^{\beta}$ and $\mathrm{F}_K\mathrm{(L,K)} = \beta\mathrm{L}^{\alpha}K^{\beta-1}$. Noting that $\beta < 1$ and $\mathrm{K} > 1$, so we have $\mathrm{F(L,K)} > \mathrm{F}_K\mathrm{(L,K)}$.

[7] This is likely to be true because this study focuses on whether a firm invests in intangible capital or not. For those that have not invested in intangible capital yet, $\mathrm{IC} = 0$ and thus $\frac{\partial \mathrm{A}}{\partial \mathrm{IC}\,\partial \mathrm{H}}$ is likely to be sufficiently large to ensure $\frac{\partial \mathrm{A}}{\partial \mathrm{IC}\,\partial \mathrm{H}} > \frac{\partial \mathrm{A}}{\partial \mathrm{H}}$.

capital. The features of innovation activities as a form of risky investment make them particularly sensitive to institutional quality (Jorde and Teece, 1990). Zhou (2014) finds that low institutional quality is harmful to R&D investment, using data from Chinese firms: in an area where intellectual property is not properly protected, a firm has a higher probability of losing some of the intangible capital it produces because its designs, R&D and business secrets are more likely to be stolen, which in turn deters R&D investment. Mathematically, we add the institutional component into equation (1) by modelling it as a rate of survival, and then we have

$$\mathrm{DMR} = IQ \times \mathrm{F(L,K)} \frac{\partial \mathrm{A}}{\partial \mathrm{IC}} - \mathrm{A}(IC, H, \theta)\mathrm{F}_K(\mathrm{L,K})$$

where IQ is the institutional quality, which indicates the survival rate of intangible capital vulnerable to thefts or knockoffs and enters the equation as a probability and hence a multiplicative term. Therefore, $IQ \times \mathrm{F(L,K)} \frac{\partial \mathrm{A}}{\partial \mathrm{IC}}$ is the expected marginal return of intangible investment. Then we obtain

$$\frac{\partial \mathrm{DMR}}{\partial \mathrm{IQ}} = \mathrm{F(L,K)} \frac{\partial \mathrm{A}}{\partial \mathrm{IC}} > 0$$

which forms the basis for Hypothesis 3:

Hypothesis 3. Lower institutional quality reduces the probability of a firm investing in intangible capital vulnerable to thefts or knockoffs.

Another factor to be considered is market competition. The impact of competition on firms' effort to innovate is not yet conclusive in the literature. Some studies have found that market competition exerts a negative effect on firms' incentives to increase their R&D efforts (Loury, 1979; Martin, 1993), while others find that only firms with low R&D productivity tend to exhibit a lower level of R&D efforts when facing increased market competition (Lee, 2009). A non-linear relationship (inverted U-shape relationship) is also proposed by a previous study based on UK data (Aghion et al., 2005) but a later study (Hashmi, 2013) finds the non-linear relationship non-exists in US data. While the theories of Aghion et al. (2005) and Hashmi (2013) both agree that firms are less likely to engage in innovation activities when facing a competitive market, their main difference is whether the relationship between competition and innovation within moderate to medium competition is negative or not, which needs further evidence from other economies. In China, firms facing a competitive market are likely to earn a low markup from innovating and often earn zero economic profit and hence are not able to fund investment in intangibles. In contrast, firms facing an oligopoly market are likely to earn a high markup from innovation, and thus more likely to invest in intangibles. Firms facing a market between oligopoly and competitive might demonstrate a medium propensity to invest in intangibles. This mechanism is summarized in Hypothesis 4.

Hypothesis 4. Firms facing a competitive market are less likely to invest in intangible capital while firms facing an oligopoly market are more likely to invest in intangible capital, compared with firms facing a market between competitive and oligopoly.

2.3 Data and empirical strategy

Data used in this study were retrieved from the China Enterprise Survey 2012 conducted by the World Bank. This dataset covers data in 2011 and consists of 1,523 private sector[8] manufacturing firms from 25 major cities[9] in China, with observations

[8] Using firms from the private sector has the advantage of better reflecting the economic incentives of firms because state-owned firms may invest in intangibles for political purposes.

[9] The 25 cities are as follows: Hefei, Beijing, Guangzhou, Shenzhen, Foshan, Dongguan, Shijiazhuang,

covering all manufacturing industries[10]. The observations are distributed relatively evenly across cities, with approximately 50 observations per city and 100 observations per stratified sector[11]. The sample was selected using stratified random sampling, which ensures that the sample is unbiased. This dataset provides valuable measurements of intangible investment as well as firm-level information necessary for the estimation of the production function.

The definition of intangible investment used in this study follows that of Corrado et al. (2009). The advantage of using this definition is that it covers a broad range of expenditure that boosts firm productivity and is therefore a relatively comprehensive definition. According to Corrado et al. (2009), intangible capital consists of three main categories: computerized information (mainly software), intellectual property (R&D) and economic competency (advertising, staff training and organization capital). Regarding firms' intangible investment behaviour, there are two interesting questions to answer. One is what determines whether a firm invests in a specific type of intangible or not and the other is what determines the amount of investment in a specific type of intangible. The unique feature of this firm-level survey is that it includes various questions that are highly related to intangible investment. For example, whether a firm invests in internal R&D or not is manifested by the question 'In the last three years, did

Tangshan, Zhengzhou, Luoyang, Wuhan, Nanjing, Wuxi, Suzhou, Nantong, Shenyang, Dalian, Jinan, Qingdao, Yantai, Shanghai, Chengdu, Hangzhou, Ningbo, Wenzhou.

[10] The industry classification is as follows: food, tobacco, textiles, garments, leather, wood, paper, recorded media, refined petroleum product, chemicals, plastics & rubber, non-metallic mineral products, basic metals, fabricated metal products, machinery and equipment, electronics, precision instruments, transport machines, furniture, recycling.

[11] Stratified sector classification is a less detailed classification that includes Food, Textiles, Garments, Chemicals, Plastics & rubber, Non-metallic mineral products, Basic metals, Fabricated metal products, Machinery and equipment, Electronics, Motor vehicles and Other manufacturing. The use of stratified sectors is to avoid the problems of insufficient observations in certain industries.

this establishment spend on research and development activities within the establishment?' Table 1 summarizes different measurements of intangible investment to facilitate future use of the dataset by other researchers.

Table 1 Measuring intangible investment behaviour

Category	Variable types	Relevant questions in the questionnaire
R&D (Overall)	Dichotomous and continuous	CNO.3, CNO.4, CNO.5, CNO.6
R&D (Internal)	Dichotomous and continuous	CNO.3, CNO.4
R&D (Outsourced)	Dichotomous and continuous	CNO.5, CNO.6
Organization investment[12]	Dichotomous and continuous	CNo14b, CNo14c, CNo14d, CNo15b, CNo15c, CNo15d
Software investment	Dichotomous	CNo12e

Notes: The questionnaire used in the Chinese enterprises survey can be downloaded from http://microdata.worldbank.org/index.php/catalog/1559.

Source: Authors' own construction.

Before we start to explore the intangible investment of firms, it is helpful to examine the relationship between intangible investment and firm productivity. We assume a typical firm has two inputs – physical capital and labour. The translog approach (Kim, 1992) is then used to estimate total factor productivity (TFP) of the firm. Compared with the Cobb-Douglas approach, the translog approach removes assumptions of constant output elasticities. Specifically, the model specification is as follows:

$$y_i = \beta_k k_i + \beta_l l_i + \beta_{lk} l_i k_i + \beta_{ll} {l_i}^2 + \beta_{kk} {k_i}^2 + a + \varepsilon_i \tag{2}$$

All variables are in natural logarithm values. y is the value added, measured as revenue minus cost of intermediate input; k is physical capital; l is labour; a is the intercept

[12] Organization investment is defined as investment in operation and management improvement as well as staff training. Advertising has not been included due to insufficient data.

term, which captures the baseline productivity of all firms. Physical capital is measured by the reported fixed assets, and labour is measured by the reported number of full-time employees. TFP is measured by the error term ε_i.

As discussed in section 2, firm-level evidence for emerging countries on how intangible capital contributes to TFP growth is rare. Therefore, it is necessary to examine the relationship between TFP and intangible investment using data from Chinese firms. Due to data availability, software investment and organization investment are in the form of dummy variables. Besides intangibles, information and communication technology (ICT) capital (Atzeni and Carboni, 2006) and exports (Arnold and Hussinger, 2005; Wagner, 2007) have also been found to have significant impacts on firms' productivity and therefore control variables for ICT investment and export are necessary for the empirical model. Moreover, Brynjolfsson et al. (2002) argue that the use of new software is often accompanied by organizational redesign and changes in the skill mix of employees based on data from US firms. Adopting new software indicates changes in the production process, which requires investment in organization. It is important to examine whether such a complementary relationship is present in the case of Chinese firms. Therefore, an interaction term between organization investment and software investment is also included in the empirical model. The model specification is hence as follows:

$$TFP_i = \beta_1 IT\_intensity_i + \beta_2 R\&D\_intensity_i + \beta_3 software_i + \beta_4 organization_i$$
$$+\beta_5 organization_i \times software_i + \beta_6 export_i + industry\_effects + a + \varepsilon_i \qquad (3)$$

where $IT\_intensity$ is the annual costs of IT equipment investment divided by the fixed assets; $R\&D\_intensity$ is internal R&D expenditure[13] divided by the fixed assets; $software$ is a dummy variable indicating whether a firm invests in software or not; $organization$ is a dummy indicating whether a firm invests in organization capital or not; $organization \times software$ is the interaction term between $organization$ and $software$; $export_i$ is a dummy indicating whether a firm exports or not; $industry\_effects$ consists of a number of dummies indicating the industry a firm belongs to; a is the intercept term. Of all the variables, $IT\_intensity$ and $R\&D\_intensity$ are in natural logarithm values.

To study the determinants of intangible investment, we adopt two steps. The first is to study the propensity to invest in intangibles and the second is to study the quantity of investment. Four factors discussed in section 2 will be examined. They include human capital, market competition, firm size and institutional quality. That is,

$$Intangible\_d_{p,i} = \beta_1 human\_capital_i + \beta_2 competitive\_market_i + \beta_3 oligoly\_market_i + \beta_4 size_i + \beta_5 institution_i + industry\_effect + \beta_6 export_i + a + \varepsilon_i \quad (4)$$

$$Intangible\_q_{p,i} = \beta_1 human\_capital_i + \beta_2 competitive\_market_i + \beta_3 oligoly\_market_i + \beta_4 size_i + \beta_5 institution_i + industry\_effect + \beta_6 export_i + a + \varepsilon_i \quad (5)$$

$Intangible\_d_{p,i}$ stands for whether firm i invests in intangible investment p or not; $Intangible\_q_{p,i}$ refers to the amount firm i invests in intangible investment p;

[13] The reason we exclude outsourced R&D is that it significantly limits the number of observations due to too many zero observations.

$human\_capital_i$ is the average human capital of a firm, measured by the average educational years of permanent workers; $market\_competition_i$ is a dummy indicating whether a firm faces a competitive market or not, measured by whether a firm reports its number of competitors as too many to count[14]; $oligoly\_market$ is a dummy indicating whether a firm faces an oligopoly market or not, measured by whether a firm reports its number of competitors as no more than five or not[15]; $size_i$ is the firm size, measured by the fixed assets of a firm; $institution_i$ is local institutional quality, measured by the NERI Index of Marketization for China's provinces published by the National Economic Research Institute (NERI) (Fan et al., 2011). The NERI Index of marketization is a common tool used as an indicator of China's provincial institution quality. It consists of five dimensions: how strong the government intervention is, how intensive the economic activities of non-state-owned enterprises (non-SOE) is, development of the product market, development of the factor market, and development of the legal system and intellectual property protection. The surveyed enterprises are all located in the capital city or major cities of a province and therefore it is appropriate to use the provincial index to represent the institutional quality of a city. $export_i$ indicates whether a firm exports or not, which is an important control variable. Many studies find that whether a firm exports or not is positively correlated with its innovation (Baldwin and Gu, 2004; Becker and Egger, 2013; Roper and Love, 2002; Wakelin, 1998) and therefore controlling for export is necessary. $industry\_effect$ symbolizes the industry fixed effect. Of all the variables, $human\_capital_i$, $size_i$ and

[14] Different firms might have different standard for 'too many to count'. However, this variable at least indicates whether a firm views itself as facing a competitive market.

[15] One of the key features of an oligopoly is that the market is dominated by a small number of firms. Five is a reasonable threshold and varying the threshold number does not change the results.

$institution_i$ are in natural logarithm values while others are dummies.

Some key variables of interest might be subject to endogeneity. Firms may only report the competitors that produce similar products but neglect the producers of relevant substitutes and complements. Similar products might often require a similar level of intangible investment (entry barrier), which leads to estimation being biased. The reported number of competitors might also be determined by intangible investment levels because firms might only consider firms with similar intangible investment levels as competitors. When it comes to institutional quality, it may be associated with unobserved social-economic characteristics that might be correlated with intangible investment. Nee and Opper (2012) also suggest that institutional quality might be endogenously determined by the needs of firms: when increasing number of firms are engaged in innovation activities, government may have incentives to establish proper institutions to accommodate the changes.

Therefore, two sets of instruments are respectively proposed to partially resolve the relevant issues. First, the percentage of total annual sales of goods paid after delivery (firms as the seller, selling final products) and the percentage of materials or services input paid after delivery (firms as the buyer, buying intermediate goods). On the one hand, these two variables provide information on the common payment type within the industry, which is often custom-based and not able to be influenced by an individual firm in the short run; on the other hand, they reveal objective historical information on competition within the final product market and intermediate product market, with both substitutes and complements being considered. Moreover, there is no direct link between these two variables and intangible investment except through market competition, which is an important criterion that instruments must satisfy. Second, the mortality rates during the Great Famine (1959 – 1961) are used as instruments for institutional quality, following Wang et al. (2014). As Wang et al. (2014) argue, a region's ability to fight natural disasters is correlated with its institutional quality at the time. According to Acemoglu and Johnson (2005), institutions are path dependent and thus a region with weaker institutions in the past is likely to have weaker institutions today. Furthermore, the mortality took place during the planned economy period when all economic activities were guided by the central government instead of market forces, which is uncorrelated with today's social-economic characters that might be associated with intangible investment. As a result, mortality rates during the Great Famine are qualified instruments for institutional quality in this context.

Table 2 shows the descriptive statistics of the variables of interest. Heterogeneity of firms in their investment in intangibles can be seen from the range of the statistics. 41% of the firms have invested in R&D recently and most of the R&D is internal since the ratio of firms with overall R&D investment and the ratio of firms with internal R&D investment are considerably close. When it comes to organization and software investment, 77% and 45% of the firms have invested, respectively. 67% of the firms face a competitive market while 7% of the firms face an oligopoly market. The variation in firm size as manifested by labour quantity and tangible quantity is large.

Table 2 Descriptive statistics (overall)

Variable	Obs	Mean	Std. Dev.	Min	Max
R&D (Overall, dichotomous)	1,550	0.406452	0.491329	0	1
R&D (Overall, continuous)	1,024	1987827	3.01e+07	0	9.00e+08
R&D (Internal, dichotomous)	1,550	0.388387	0.487541	0	1
R&D (Internal, continuous)	1,550	1548257	1.17E+07	0	3.00E+08
R&D (Outsourced, dichotomous)	1,550	0.107742	0.310154	0	1
R&D (Outsourced, continuous)	1,550	657719.4	1.54E+07	0	6.00E+08
Organization investment (Dichotomous)	1,550	0.767097	0.422818	0	1
Organization investment (Continuous)	1,550	1.628387	0.862282	0	3
Software (Dichotomous)	1,550	0.445161	0.497144	0	1
ln(VA)	1,545	16.32839	1.63567	11.28978	24.15725
ln(K)	1,346	15.44729	1.857326	5.713733	25.10554
ln(L)	1,550	4.451218	1.285376	1.609438	10.31642
ln(Human capital)	1,530	2.298944	0.198954	0	2.890372
Competitive	1,550	0.671613	0.469778	0	1
Oligopoly	1,550	0.066452	0.24915	0	1
ln(IQ)	1,550	2.259194	0.172053	1.983756	2.4681
ln(RD_intensity)	459	-2.4982	1.83159	-6.95655	3.35241
ln(IT_intensity)	1,169	-3.81444	2.130712	-10.5969	7.408631

Source: Authors' own calculation.

2.4 Pattern of intangibles investment in China

To shed more light on the pattern of Chinese firms' investment in intangibles, we look at both the geographical and sectoral distribution of intangibles. Figures 1 to 3 demonstrate the percentage of firms investing in intangibles in various cities in China. The larger the size of the circle, the higher the percentage of firms with positive investment in intangibles. From Figure 1, we can see that the percentage of firms investing in R&D is higher in Pearl River Delta and Yangtze River Delta than those in northern China. Firms in Chengdu, Shenyang, Qingdao, Tangshan and Shijiazhuang have significantly lower percentages compared with other cities in this sample. Figure 2 shows that the percentage of firms investing in organization capital is relatively more even across different cities. Figure 3 shows that software investment has a similar pattern to R&D investment. Overall, firms in Chengdu, Shenyang, Qingdao, Tangshan and Shijiazhuang have low intangible investment percentages among all cities.

Figure 1 Percentage of firms investing in R&D (City level)

Source: Authors' own construction.

Figure 2 Percentage of firms investing in organization capital (City level)

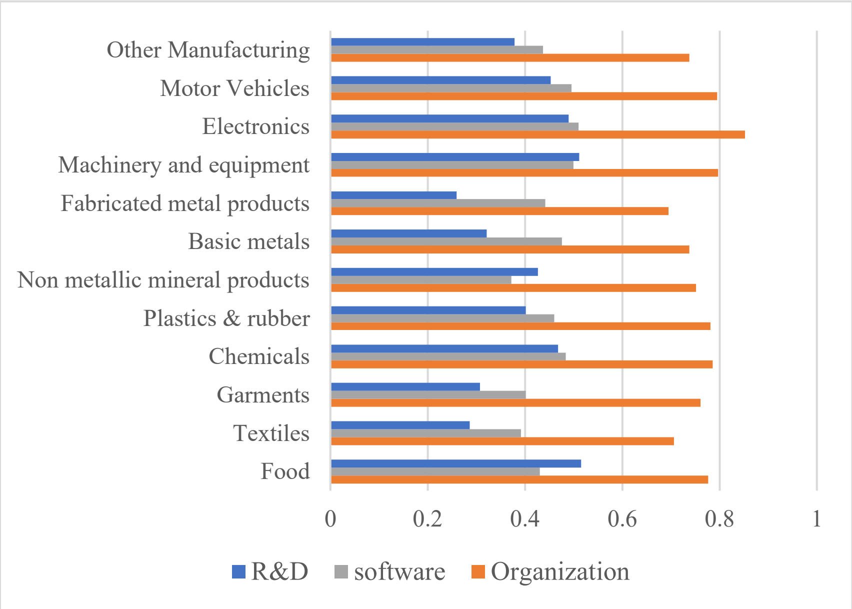
Source: Authors' own construction.

Figure 3 Percentage of firms investing in software (City level)

Source: Authors' own construction.

Figure 4 depicts the percentage of firms investing in intangibles in various sectors. Amongst the three components of intangibles, organization investment is most evenly distributed across sectors and most commonly made by firms compared with the other two components, with about 70% of firms investing in organization capital. Software investment is less evenly distributed across sectors compared with organization investment, and around 50% of firms invest in software. There is higher variation between sectors in the percentage of firms with positive R&D investment. Among all sectors, fabricated metal products, basic metals, garments and textiles have low percentages of R&D investment.

Figure 4 Percentage of firms investing in intangibles (sectoral level)



Source: Authors' own construction.

With the above knowledge of the overall pattern of intangibles investment by firms in China, we will now conduct firm-level analysis to delve into the underlying economic mechanisms of firms' investment in intangibles.

2.5 Firm-level evidence

In this section, we report the empirical findings on testing the four hypotheses about the determinants of intangible investment developed in section 2 and how intangibles impact firm productivity. Probit regressions are used to examine how determinants influence the probability of investing in intangibles, while Tobit regressions are adopted to examine how determinants affect the amount of intangible investment, accounting for the zero-value observations of intangible investment. Table 3 illustrates the determinants of software investment and organization investment while Table 4 presents the determinants of R&D investment, both in the form of marginal effects. All the factors mentioned in section 2 are found to play an important role in determining intangible investment.

Table 3 Determinants of software investment and organization investment (marginal effects)

	Probit				Tobit	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	software	software(IV)	organization	organization(IV)	organization	organization(IV)
HC	0.248***	0.132***	0.0710	0.171	0.226	0.171
	(0.0802)	(0.0362)	(0.0562)	(0.114)	(0.146)	(0.114)
CM	-0.0956***	-0.418***	-0.113***	-0.174***	-0.180***	-0.174***
	(0.0313)	(0.0146)	(0.0284)	(0.0541)	(0.0691)	(0.0541)
Oligo	0.136**	0.205***	-0.129**	-0.459***	-0.242*	-0.459***
	(0.0596)	(0.0412)	(0.0511)	(0.101)	(0.130)	(0.101)
Size	0.0476***	0.0275***	0.0367***	0.135***	0.165***	0.135***
	(0.00719)	(0.00435)	(0.00626)	(0.0123)	(0.0158)	(0.0123)
Institution	0.111	0.225***	-0.132*	-0.499***	-0.686***	-0.499***
	(0.0776)	(0.0760)	(0.0723)	(0.136)	(0.173)	(0.136)
Export	0.118***	0.0592***	0.0650**	0.146**	0.185**	0.146**
	(0.0330)	(0.0186)	(0.0315)	(0.0581)	(0.0745)	(0.0581)
Observations	1,297	1,298	1,297	1,298	1,298	1,298
Industry FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

HC stands for human capital; CM refers to whether a firm faces a competitive market or not; Oligo indicates whether a firm faces an oligopoly market or not; Size is the size of a firm, measured by the amount of fixed asset; Institution stands for the institution score of the province where a city is located.

Source: Authors’ own calculation.

Table 4 Determinants of R&D investment (marginal effects)

	Probit						Tobit					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	R&D	R&D(IV)	internal R&D	internal R&D(IV)	outsourced R&D	outsourced R&D(IV)	R&D	R&D(IV)	internal R&D	internal R&D(IV)	outsourced R&D	outsourced R&D(IV)
HC	0.0942	0.275	0.155**	0.461**	-0.164***	-0.998***	-1.960e+07	1.074e+06	1.76E+06	1.657e+06	-4.892e+07***	-2.114e+06
	(0.0646)	(0.190)	(0.0638)	(0.193)	(0.0498)	(0.216)	(2.046e+07)	(5.074e+06)	(1.73E+06)	(1.723e+06)	(1.179e+07)	(2.292e+06)
CM	-0.0767***	0.0434	-0.0891***	0.205	-0.0186	-0.0714	-1.988e+07*	-991,190	6.31E+05	1.660e+06	-5.789e+06	1.308e+06
	(0.0294)	(0.333)	(0.0289)	(0.305)	(0.0198)	(0.464)	(1.106e+07)	(2.464e+06)	(8.16E+05)	(0)	(6.213e+06)	(1.114e+06)
Olio	0.154***	0.965***	0.147***	0.686*	0.0528	0.485	7.067e+07***	2.158e+07***	5.88E+06***	6.460e+06***	3.228e+07***	8.465e+06***
	(0.0563)	(0.324)	(0.0556)	(0.360)	(0.0345)	(0.335)	(1.788e+07)	(4.988e+06)	(1.53E+06)	(2.125e+06)	(9.795e+06)	(2.512e+06)
Size	0.0759***	0.226***	0.0744***	0.223***	0.0250***	0.141***	1.925e+07***	2.698e+06***	1.47E+06***	1.458e+06***	8.039e+06***	661,531***
	(0.00735)	(0.0219)	(0.00722)	(0.0226)	(0.00543)	(0.0264)	(2.597e+06)	(567,584)	(1.86E+05)	(184,388)	(1.471e+06)	(246,948)
Institution	0.302***	1.089***	0.327***	1.015***	0.00984	1.079***	7.434e+07**	1.082e+07*	2.55E+06	2.625e+06	1.102e+07	2.885e+06
	(0.0734)	(0.318)	(0.0725)	(0.324)	(0.0491)	(0.412)	(3.056e+07)	(6.181e+06)	(2.04E+06)	(2.793e+06)	(1.686e+07)	(3.805e+06)
Export	0.117***	0.339***	0.107***	0.319***	0.0838***	0.467***	4.991e+07***	7.526e+06***	2.96E+06***	2.699e+06***	2.723e+07***	2.034e+06*
	(0.0308)	(0.0954)	(0.0303)	(0.0947)	(0.0182)	(0.112)	(1.083e+07)	(2.738e+06)	(8.79E+05)	(909,370)	(6.082e+06)	(1.166e+06)
Observations	1,297	1,298	1,297	1,298	1,297	1,298	930	900	1,298	1,298	1,298	1,298
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

HC stands for human capital; CM refers to whether a firm faces a competitive market or not; Oligo indicates whether a firm faces an oligopoly market or not; Size is the size of a firm, measured by the amount of fixed asset; Institution stands for the institution score of the province where a city is located.

Source: Authors' own calculation.

On Hypothesis 1, the results show that a firm of a larger size is more likely to invest in intangibles. On average, a 1% increase in firm size is respectively associated with a 0.05 percentage point increase in the probability of investing in software, a 0.07 percentage point increase in the probability of investing in R&D, a 0.08 percentage point increase in the probability of investing in internal R&D, a 0.03 percentage point increase in the probability of investing in outsourced R&D and a 0.04 percentage point increase in the probability of investing in organization capital. If considering the results based on instruments, the probability change is larger for R&D and organization investment but smaller for software investment. Intangible capital can be used firm-wide and has economy of scale. Therefore, it is not surprising that a firm of larger size is more likely to invest in intangibles.

On Hypothesis 2, it is found that human capital significantly increases the propensity of investing in software and internal R&D but insignificantly increases overall R&D and significantly decreases outsourced R&D. On average, a 1% increase in average educational years of permanent workers is respectively associated with a 0.25 percentage point increase in the probability of investing in software, a 0.09 percentage point increase in the probability of investing in R&D, a 0.16 percentage point increase in the probability of investing in internal R&D, a 0.16 percentage point decrease in the probability of investing in outsourced R&D and a 0.07 percentage point increase in the probability of investing in organization capital. When it comes to IV regressions, the results are generally robust although the coefficient is smaller for software investment while larger for R&D and organization investment. While human capital generally promotes intangible investment, it encourages a firm to internalize its R&D, as indicated by the negative sign of the outsourced R&D. A possible reason is that human capital lowers the costs of R&D and therefore a firm is less likely to outsource its R&D.

Looking at Hypothesis 3, we find that institutional quality significantly affects intangible investment. A 1% increase in institutional quality is associated respectively with a 0.11 percentage point increase in the probability of investing in software, a 0.30 percentage point increase in the probability of investing in R&D, a 0.33 percentage point increase in the probability of investing in internal R&D, a 0.01 percentage point increase in the probability of investing in outsourced R&D and a 0.13 percentage point decrease in the probability of investing in organization capital. The results from the IV approach remain generally robust with the effects larger in all types of intangible investment. While better institutional quality leads to a higher propensity to invest in intangibles, better institutional quality decreases the propensity of investing in organization capital. One possible reason for this is that the baseline operation efficiency is correlated with the external institutional quality. Firms do not exist in vacuum and therefore are influenced by the external environment. The effects of external environment on firms' innovation activities or organization investment have been well documented (Damanpour and Schneider, 2006; Kong, 2008). However, the effects of external institutional quality on organization investment have not been well studied. Institutional quality, including the degree of government intervention in enterprise activities, spillover effects of the advanced management practices from FDI, law enforcement and rule awareness are likely to significantly impact on the baseline operation efficiency. Specifically, when governments constantly intervene in the operational activities of enterprises, when the spillover effects of advanced management practices from FDI are high, or when the rule awareness of workers is low, enterprises are more likely to invest in organization capital to improve operational efficiency. Therefore, when external institutional quality is low, the return from organization investment is likely to be high and thus the probability of investing in organization capital is high; when external institutional quality is high, the return from organization investment is likely to be low and thus the probability of investing in organization capital is low.

In terms of Hypothesis 4, the results suggest that a firm facing a competitive market has a lower probability of investing in intangibles as well as a lower amount of investment in intangibles than a firm facing moderate market competition. On average, a firm facing a competitive market respectively has a 9.6 percentage point lower probability of investing in software, a 7.7 percentage point lower probability of investing in R&D, a 8.9 percentage point lower probability of investing in internal R&D, a 1.9 percentage point lower probability of investing in outsourced R&D and a 11.3 percentage point lower probability of investing in organization capital according to Table 3 and 4. When it comes to firms facing an oligopoly market, on average they have a 13.6 percentage point higher probability of investing in software, a 12.9 percentage point lower probability of investing in organization capital, a 15.4 percentage point higher probability of investing in R&D, a 14.7 percentage point higher probability of investing in internal R&D and a 5.28 percentage point higher probability of investing in outsourced R&D. If we look at the coefficients from the instrumental regressions, the results change slightly with larger impacts for software and organization investment. The impacts on R&D investment become insignificant for firms facing a competitive market while they become larger for firms facing an oligopoly market. The outcomes suggest a negative relationship between market competition and most intangible investment except organization investment, and an inverted U-shape relationship between market competition and organization investment. A possible reason for this is that the boost to product markup from most intangible capital is smaller when market competition is fierce (low R&D productivity, consistent with Lee, 2009), which indicates a generally negative relationship between market competition and most intangible investment. One exception is organization capital, which often helps reduce operating costs instead of increasing product markup. When competition is too fierce, firms might lack relevant economic resources to invest in organization, and when competition is limited (oligopoly), firms might tend to increase product markup by investing in other types of intangibles instead of cutting costs through organization investment. As a result, propensity to invest in organization may peak when firms are facing moderate competition. As mentioned earlier, the existing literature has intensively discussed the impacts of market competition on innovation. Some argue that fierce market competition erodes returns from innovations (Loury, 1979; Martin, 1993; Roberts, 1999) while others argue that the effects of market competition are beneficial for innovation (Bertschek, 1995; Blundell et al., 1995; Lee and Wilde, 1980; Nickell, 1996) or the effects are two-sided (Aghion et al., 2005; Lee, 2009). However, empirical evidence for emerging economies is lacking. This finding contributes to this strand of literature by providing new evidence from Chinese firms.

Apart from the four hypotheses mentioned earlier, exporting has been found to be an important factor of intangible investment behaviour, which is consistent with the existing literature (Baldwin and Gu, 2004; Becker and Egger, 2013; Roper and Love, 2002; Wakelin, 1998). Export firms on average have an 11.8 percentage point higher probability of investing in software, a 6.5 percentage point lower probability of investing in organization, an 11.7 percentage point higher probability of investing in R&D, a 10.7 percentage point higher probability of investing in internal R&D and an 8.38 percentage point higher probability of investing in outsourced R&D.

When it comes to the amount of intangible investment, the results are similar, including those derived from IV regressions. According to Tables 3 and 4, size remains significant, which indicates a positive correlation between size and the amount of intangible investment. As for human capital, it generally increases the amount of intangible investment, but its effect is either weakly significant or insignificant. Higher institutional quality is likely to increase R&D expenditure, including overall, internal and outsourced expenditure, but the effect is either insignificant or weakly significant. However, higher institutional quality significantly reduces the intensity of organization investment, which is consistent with the results of probit models. The effects of market competition on intangible investment are generally insignificant except on organization investment and R&D. The effects of export remain robust across all models.

Table 5 shows the relationship between various intangible investments and TFP of firms. The contributions of various intangible investments to TFP[29] are generally significant across all models. According to models (1) to (4) in Table 5, a 1% increase in IT equipment intensity and R&D intensity is respectively associated with 0.09% and 0.15% increase in firm productivity; a firm with software investment on average has 9% higher productivity than that without; a firm with organization investment on average has 10.5% higher productivity than that without; an export firm on average has 15% higher productivity than that without. If all types of intangible investments are incorporated in the estimation, software investment and export become insignificant. Moreover, the interaction between software investment and organization investment is also significant, which indicates a complementary effect between these two factors. Specifically, the productivity boost from organization investment of a firm with software investment is 0.63 higher than that of a firm without software investment and vice versa; investing in software without investing in organization capital even has a negative effect on firm productivity.

[29] TFP of firms is calculated using the translog approach according to equation (2) and results are available upon request from the authors.

Table 5 Intangible investment and TFP

	log(TFP)							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(IT_intensity)	0.0944***				0.0704**	0.0701**	0.0737**	0.0811**
	(0.0141)				(0.0331)	(0.0331)	(0.0325)	(0.0327)
log(R&D_intensity)		0.150***			0.0982***	0.0940***	0.0942***	0.0897**
		(0.0251)			(0.0354)	(0.0354)	(0.0352)	(0.0352)
software			0.0907*			0.142*	0.0830	-0.506**
			(0.0520)			(0.0854)	(0.0883)	(0.233)
Organization				0.105*			0.345***	0.204*
				(0.0557)			(0.111)	(0.116)
Organization*software								0.632**
								(0.246)
Export	0.148**	0.157*	0.160**	0.167***	0.138	0.115	0.102	0.114
	(0.0635)	(0.0888)	(0.0635)	(0.0632)	(0.0944)	(0.0988)	(0.0979)	(0.0982)
Constant	0.0512	0.0952	-0.262	-0.313	0.103	0.00883	-0.280	-0.146
	(0.189)	(0.284)	(0.195)	(0.203)	(0.292)	(0.289)	(0.302)	(0.304)
Observations	1,165	458	1,342	1,342	405	405	405	405
R-squared	0.075	0.137	0.035	0.035	0.154	0.159	0.170	0.176
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own calculation.

2.6 Conclusion and policy implications

Intangibles have been identified as an important source of productivity improvement and economic growth for developed economies. The determinants of firms' investment in intangibles are mostly researched for these economies as well. In this paper, we contribute to this strand of literature by focusing on the case of China, one of the largest emerging economies. We describe the pattern of intangible investment by Chinese firms, reveal the determinants of intangible investment and analyse how intangibles affect firm productivity.

The results of our estimates confirm the four hypotheses developed from the theoretical framework in section 2. We find that human capital, size and institutional quality generally increase both the propensity and quantities of intangible investment and market competition generally decreases the propensity and quantities of intangible investment, which is consistent with Loury (1979), Martin (1993) and Hashmi (2013) but different from Aghion et al. (2005). Specifically, firms facing an oligopoly market are more likely to invest in intangibles while firms facing a competitive market are less likely to invest in intangibles. The only exception is organization investment, where an inverted U-shape relationship with market competition is identified. This indicates that the propensity to invest in organization capital may peak when firms are facing moderate market competition. Evidence on the propensity is more statistically robust than that on quantities. One interesting finding is that higher human capital is associated with a lower propensity for outsourced R&D, which is consistent with the assumption in section 2 that higher human capital can lower the costs of producing intangible investment. Another interesting discovery is that better institutional quality is associated with lower organization investment. A possible reason for this is that institutional quality is associated with the baseline organization capital and further investment is unlikely to improve productivity much if the baseline capital is high.

Having explored the determinants of investment in intangibles, this study continues to examine the positive impacts of various intangible investment and ICT investment on the productivity of Chinese firms. It is found that the three components of intangibles, that is, software investment, R&D investment and organization investment, as well as ICT investment, are significantly positively correlated with firm productivity, and there is a complementary effect between organization investment and software investment.

Our findings also provide important implications for policy-making in emerging economies. Emerging economies are often trying to climb up the global value chain and therefore need to accumulate intangible capital to improve value added of product and productivity. Policies that encourage firms to build up proprietary technology and knowledge of production and thus enable firms to move away from highly competitive segments of the market, increase education and human capital, and improve institutional quality such as strengthened protection of property rights in general and intellectual property rights in particular, are likely to encourage intangible investment by firms and boost the productivity of firms as a result.

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3. Organization investment in a transitional economy: The role of ownership control type

Organization capital as an important production factor has been well studied in developed countries but has received little attention in transitional economies. This study aims to fill this gap with data from Chinese listed firms. First, this study confirms the importance of organization capital in firm production in China by providing some empirical evidence. Second, this study confirms the interaction between ownership control type and organization capital in the context of a transitional economy. The study finds that state-owned enterprises (SOEs) invest more in organization capital due to low employee turnover but have a lower effect of organization capital in improving firms' performance compared with that of private enterprises. This finding is supported by a simple theoretical model as well as empirical evidence and strengthens the importance of deepening the SOE reforms in China.

3.1 Introduction

Intangible capital has become an increasingly important production factor in determining economic growth in recent years. It is therefore not surprising that the literature has devoted much attention to its role in economic growth (Awano et al., 2010; Borgo et al., 2013; Chun and Nadiri, 2016; Corrado et al., 2013; Corrado and Hulten, 2010; Fukao et al., 2009; Haskel and Wallis, 2013; Marrano et al., 2009; Miyagawa and Hisa, 2013; van Ark et al., 2009). Organization capital, which is an important component of intangible capital, has also received much attention (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2014, 2013; Tronconi and Marzetti, 2011). Different from other intangible capital, organization capital is embodied in firms' key employees, which indicates that firms risk losing some of this capital when key employees leave (Eisfeldt and Papanikolaou, 2013). Given the fact that organization capital is embodied in firms' key employees, it is likely that the decision to invest in organization capital is affected by employee turnover, and the contribution of organization capital to firms' productivity is influenced by firms' institutions. For instance, if turnover of employees in a firm is high, then the firm may be less willing to invest in organization capital; if a firm has institutions that prevent incompetent key employees from being demoted or fired, the efficiency of organization capital is likely to be low. However, interactions between organization capital, turnover of employees and institutions of firms have received little attention and this study aims to fill this gap.

Testing the effects of employee turnover on organization capital investment as well as the impacts of institutions on the efficiency of organization capital requires significant heterogeneity in institutions and employee turnover. The prevalent existence of state-owned enterprises[1] (SOEs) in a transitional economy like China provides a valuable opportunity to study these interactions. There is still a large group of SOEs listed in the stock market of China. In 2012, the market value of those companies accounted for 51.4% of the total market value of the Chinese stock market (The Central People's Government of the People's Republic of China, 2013). SOEs in China have features that are significantly different from those of private enterprises. The current human management practice in SOEs, at least partly, inherits the life-long job security, seniority-based

[1] SOEs in this paper are defined as firms controlled by central or municipal governments.

promotion and wage, and the extensive in-company welfare programs including housing, schooling, medical care et cetera from the pre-reform human management practice, and as a result the employees in SOEs demonstrate high organization commitment and the turnover of employees is relatively low (Yu and Egri, 2005). The key employees in SOEs, on the one hand, enjoy favourable salary remuneration as business leaders while on the other, are often deeply integrated into China's nomenklatura system[2] and bianzhi system[3]: they have ranks as the government officers and can become a government officer of the same rank (Brødsgaard, 2012). Consistent with Yu and Egri (2005) and Brødsgaard (2012), Shen and Lin (2009) also find that the top management turnover is significantly smaller in SOEs than private enterprises after controlling other variables using data from Chinese listed companies. What can be inferred from the literature? It is possible that the institutions embodied in the ownership control types lead to the differences in employee turnover as well as the potential differences in organization capital efficiency. In this study, I focus on one aspect of the institutions, that is, human management practice. The aforementioned human management practice implies that the life-long job security provided by SOEs makes it difficult to demote or fire incompetent key employees. Based on this implication, I construct a simple theoretical model to analyse how this feature of SOEs causes low employee turnover as well as lower organization capital efficiency and then conduct empirical analysis to test the hypothesis derived from this simple model using data from Chinese listed firms.

[2] The nomenklatura system refers to the Communist Party's governance to make appointments to key positions throughout the governmental system, as well as throughout the party's own hierarchy.
[3] Bianzhi system is a list of authorized personnel, as well as their duties and functions in government bodies, state enterprises and service organizations. Bianzhi applies to all the formal employees while nonmenklatura applies to the key positions. For details of the bianzhi system, please see Brødsgaard (2002).

Before studying the aforesaid interaction between organization capital and institutions, it is helpful to first confirm the role of organization capital in firm-level production in China, which is another contribution of this study. Although organization capital has been well documented in developed economies, relevant studies on developing economies are rare. Developing economies, different from developed economies, often have underdeveloped institutions and low human capital as well as low intangible capital stock. Organization capital as one category of intangible capital may therefore exert a different effect given the different context embodied in developing economies and this study will provide relevant firm-level evidence.

This essay is organized as follows. The next section measures firm-level organization capital in Chinese listed firms and confirms its role as a critical production factor; section 3 is a simple theoretical model on how the features of SOEs in China lead to lower employee turnover, higher organization investment as well as lower efficiency of organization capital; section 4 provides empirical evidence for higher organization capital investment as well as lower efficiency of organization capital in SOEs; section 5 is the conclusion and provides policy implications.

3.2 The role of organization capital in production: Evidence from Chinese listed companies

Before studying the interaction between the firm ownership control type and organization capital, it is important to confirm the role of organization capital in firm-level production in China. Therefore, an extended Cobb-Douglas production function with organization capital is assumed and the logarithm of both sides is taken. The following is obtained

$$\mathrm{Q_{it}} = \mathrm{A_{it}} + \beta_o \mathrm{lnO_{it}} + \beta_k \mathrm{lnK_{it}} + \beta_l \mathrm{lnL_{it}}$$

Q_{it} denotes the annual sales of a firm, O_{it} denotes the organization capital of a firm, $\mathrm{K_{it}}$ denotes the book assets of a firm and $\mathrm{L_{it}}$ denotes the number of employees of a firm. Moreover, for comparison, a standard Cobb-Douglas production function is also assumed as follows

$$\mathrm{Q_{it}} = \mathrm{A_{it}} + \beta_k \mathrm{lnK_{it}} + \beta_l \mathrm{lnL_{it}}$$

The notations are similar to the extended production function. Several estimation methods are used including Pooled OLS (POLS), fixed effects (FE) and the Levinsohn and Petrin (2003) (LP) approach. Compared with POLS and FE, the LP approach addresses the problem of estimation bias caused by unobservable productivity shocks. A key issue in production function estimation is the correlation between the un-observable productivity shocks and input levels. A firm responds to positive productivity shocks by expanding output and input. Negative shocks lead to an industry reducing output and input usage. When true, ordinary least square (OLS) estimates of production functions are likely to be biased, which leads to biased estimates of productivity. Levinsohn and Petrin (2003) address this problem by introducing a proxy for productivity shocks and then use the GMM estimation method. The proxy used in this study is the percentage change in total assets, which includes information on current investment[4] as well as the retained profits that are likely to respond positively to the productivity shock.

[4] Current investment is commonly used as a proxy for productivity shocks in Olley and Pakes (1996).

Data and methodology

Data in this study is mainly from the China Stock Market and Accounting Research Database (CSMAR). Although the stock market of China was established in December 1990, the data in this study spans from 1999 to 2013, the reason for which is that data before 1999 misses key variables used to measure organization investment. Measurement of organization capital follows relevant accounting and financial literature on organization capital (Black and Lynch, 2005; Eisfeldt and Papanikolaou, 2013) by using firms' selling, general and administrative (SG&A) expense as the proxy for organization capital investment. The perpetual inventory method is adopted to derive the amount of organization capital. The rationale behind using SG&A expenditure to measure organization capital is that a large part of it is related to the wage of management workers, staff training, consulting and IT expenses that form organization capital. The Consumer Price Index (CPI) is used as the deflator in this study following Eisfeldt and Papanikolaou (2013). Mathematically, the perpetual inventory method is summarized as follows

$$\mathrm{O}_{it} = (1-\delta)\mathrm{O}_{it-1} + \frac{\mathrm{SG\&A}_{it}}{cpi_t}$$

where δ is the depreciation rate of organization capital, which is 15%[5] following Eisfeldt and Papanikolaou (2013). cpi_t is the consumer price index[6]. To implement the law of motion of organization capital, an initial stock of organization capital has to be chosen and the method to calculate it follows Eisfeldt and Papanikolaou (2013) by using

$$\mathrm{O}_0 = \frac{SG\&A_1}{g+\delta}$$

g is chosen according to the average real growth rate of firm-level SG&A in the same

[5] The depreciation of 15% is equal to the depreciation rate used by the BEA in its estimation of R&D capital in 2006 and changes in the depreciation rate from 10% to 50% do not change the results (Eisfeldt and Papanikolaou, 2013).

[6] The base year is 1990.

industry[7]. Compared with Eisfeldt and Papanikolaou (2013) who use the average real growth rate of overall firm-level SG&A, the method used in this study better reflects the growth pattern of organization capital investment within a specific industry and is therefore likely to be more accurate. Observations with zero organization capital are dropped following Eisfeldt and Papanikolaou (2013).

Production function estimation

Due to differences in production structure, observations are split[8] into two groups, namely, non-service and service groups[9], which ensures the results are robust across different industries. Table 1 reports the results for the non-service group while those for the service group are reported in Table 2. These two tables tell a consistent story and several points deserve mention. First, organization is a significant production factor across all models as well as the two industrial groups. Second, adding organization capital consistently drags down the coefficients of both tangible capital and labour and the drag-down is larger for labour, which indicates that although organization capital is positively correlated with both labour and tangible capital, it correlates more with labour. Third, the input elasticity of organization capital is higher in the service-group than the non-service group, which is consistent with the labour-intensity feature of the service group.

What do all these points imply? While organization capital is an important production

[7] The industry classification is obtained according to the level 2 classification of Shanghai Stock Exchange and Shenzhen Stock exchange, which divides all firms into 160 industries.
[8] The output elasticity of production factors is likely to differ between the two groups. Estimating separately would reveal the potential heterogeneous role of organization capital.
[9] Since the list of industry classification includes 160 industries, the division of non-service and service groups is available upon contacting the author.

factor in China, it interacts more with labour, which is consistent with the fact that organization capital is embodied in key employees.

Given the scarcity of studies of organization capital in developing economies, it is beneficial to compare the results of Table 1 and 2 with counterparts for developed economies. The benchmark for comparison is obtained from Tronconi and Marzetti (2011). Tronconi and Marzetti (2011) use data from European listed firms and conduct similar analysis as this study. One of the significant differences in the input elasticity between European firms and Chinese firms is that input elasticity of capital is much higher while the input elasticity of labour is much lower in Chinese firms. However, the difference in input elasticity of organization capital is relatively small between Chinese firms and European firms. Some implications may be drawn from these two findings. The significant differences in the input elasticity of capital and labour might be due to differences in industrial components and production structure between China and Europe. However, the role of organization capital that is embodied in key employees is similar, at least during the data period of the two studies.

Table 1 Production function estimation: non-service group

VARIABLES	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) LP	(6) LP
log(K)	0.930***	0.765***	0.804***	0.713***	0.838***	0.833***
	(0.0177)	(0.0189)	(0.0235)	(0.0267)	(0.0586)	(0.0490)
log(L)	0.208***	0.131***	0.152***	0.120***	0.204***	0.125***
	(0.0170)	(0.0168)	(0.0225)	(0.0217)	(0.0158)	(0.0174)
log(OC)		0.281***		0.253***		0.318***
		(0.0193)		(0.0323)		(0.0187)
Constant	-0.851***	-0.694***	2.595***	1.017**		
	(0.283)	(0.252)	(0.472)	(0.488)		
Observations	10,685	10,685	10,685	10,685	6,929	6,929
Number of id	N/A	N/A	1,880	1,880	N/A	N/A
R-squared	0.830	0.848	0.796	0.803	N/A	N/A

Notes: Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. OC refers to organization capital.

Source: Author's own calculation.

Table 2 Production function estimation: service group

VARIABLES	(1) POLS	(2) POLS	(3) FE	(4) FE	(5) LP	(6) LP
log(K)	0.756***	0.613***	0.784***	0.711***	0.854***	0.870***
	(0.0235)	(0.0271)	(0.0562)	(0.0567)	(0.112)	(0.147)
log(L)	0.348***	0.195***	0.281***	0.222***	0.348***	0.180***
	(0.0226)	(0.0279)	(0.0353)	(0.0370)	(0.0291)	(0.0322)
log(OC)		0.406***		0.352***		0.448***
		(0.0396)		(0.0717)		(0.0421)
Constant	1.883***	0.219	1.825	-1.441		
	(0.463)	(0.453)	(1.286)	(1.199)		
Observations	3,665	3,665	3,665	3,665	2,355	2,355
Number of id	N/A	N/A	619	619	N/A	N/A
R-squared	0.722	0.756	0.659	0.669	N/A	N/A

Notes: Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. OC refers to organization capital.

Source: Author's own calculation.

3.3 Employee turnover and efficiency of organization capital in Chinese SOEs: A simple model

After confirming the importance of organization capital in the production of Chinese listed firms, this section discusses the interaction between organization capital and institutions. Before proceeding, it is necessary to first define the efficiency of organization capital. The efficiency of organization capital in this study refers to the contribution of a unit of organization capital to firms' performance. As mentioned before, organization capital is embodied in key employees and therefore its efficiency is likely to be influenced by institutions. The institutional features of SOEs are distinct from those of private enterprises. SOEs in China are supervised by the local or central government through the State-owned Assets Supervision and Administration Commission (SASAC) and at least partially inherit the human resource management practice from the Chinese governments. Specifically, Chinese SOEs are deeply integrated into the bianzhi system. Once an employee is recruited as a formal employee and enters the bianzhi system, it is extremely difficult to demote or fire that employee unless she or he commits serious mistakes. When it comes to private enterprises, it is easier to demote or fire an employee. How does the difference in human resource management practice lead to the possible difference in the efficiency of organization capital? It is necessary to consider the features of the job market. In reality, the job market is information asymmetric and therefore an employer can hardly understand the true value of an employee until the employee has worked for some time. As a result, it is necessary for the employer to adjust the payment to the employee after observing the true value of the employee. However, the human resource management practice in SOEs increases the difficulty in adjusting the payment and thus influences the efficiency of the economic resources paid to the key employees.

Motivated by the difference in human resource management practice between SOEs and private enterprises in China as well as inspired by the analytical framework of Greenwald (1986), a simple two-period model is proposed for analysis. The agents in this model are management workers who enter the labour force for management positions at the beginning of period one. There are two types of firms recruiting management workers in the job market, namely, SOEs and private enterprises. During period one, workers are hired and work over period one. At the end of period one, they may choose to either remain with their initial employers or change jobs. After working two periods, all employees retire. This temporal sequence of events is shown in Figure 1. Next, a few assumptions are made.

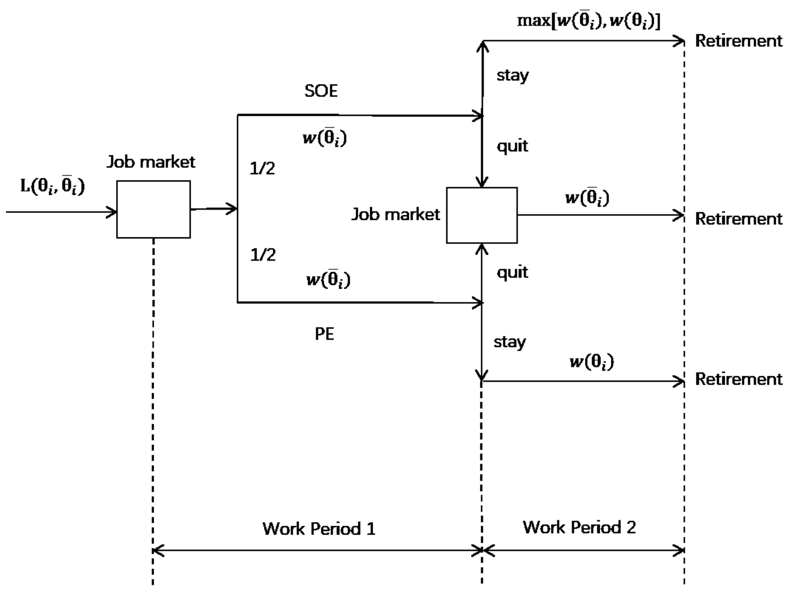

Figure 1 Timeline of the two-period model

Assumption 1. Each worker L_i is characterized by a partly observable ability measured by θ_i. Potential employers can observe the ability with an error before employing but can observe the true value after one period of employment. The error obeys a uniform distribution within $(-\alpha,\alpha)$ for the whole population but is fixed for an individual. The observed ability is denoted by $\bar{\theta}_i = \theta_i + r_i$ in period one, where r_i is the fixed error term of individual i.

Assumption 2. A firm offers wage based on the ability $\bar{\theta}_i$ it observed. Denote $w(\bar{\theta}_i)$ as the wage function. The definition of $w(\bar{\theta}_i)$ is as follows:

$$w(\bar{\theta}_i) = \sigma\bar{\theta}_i;$$

where σ is a constant wage coefficient for a worker's ability. However, the salary of a worker in a SOE is not able to be decreased in period two if the worker chooses to remain.

Assumption 3. A worker randomly enters a management position of a private enterprise or an SOE if the wage offered is the same.

Assumptions 4. The efficiency of organization capital is measured by the ratio of total ability to the total wage for management positions, that is,

$$\mathrm{E} = \frac{\sum_{i\in I}\theta_i}{\sum_{i\in I}w_i},$$

where I is the index set of management workers of a firm in a single period.

Assumption 1 captures the fact that employers can observe the ability of the employees by some signals such as education, performance at interview, et cetera but the observation is biased. Assumption 2 captures the difference in the wage policy between private enterprises and SOEs. In SOEs, once the salary is set it cannot be decreased. Assumption 3 captures the feature of the contingent nature of job seeking[10]. Assumption 4 expresses

[10] Job market candidates are myopic and cannot foresee what will happen in period two at the beginning of period one. This is a relatively strong assumption that aims to simplify the model.

the efficiency of firms' organization capital in terms of ability per unit of currency.

At the beginning of period two, an employee decides whether to remain in the original firm or not. The decision rule is to choose the path that maximizes the wage in period two. According to assumption two, employers know the true ability of employees at the beginning of period two. In private enterprises the wage of workers will be adjusted to reflect their true ability while in SOEs only the wage of undervalued workers will be adjusted to reflect their true ability because wage cannot be decreased in SOEs. If they choose to leave an enterprise and enter the job market again, they will be offered a salary based on their observed ability, that is, $w(\theta_i + r_i)$ and a non-zero reallocation cost c will be incurred[11]. Thus, the net benefit of quitting in private enterprises is:

$$w(\theta_i + r_i) - w(\theta_i) - c$$

That of quitting in SOEs is:

$$\begin{cases} w(\theta_i + r_i) - w(\theta_i + r_i) - c \; if \; r_i > 0 \\ w(\theta_i + r_i) - w(\theta_i) - c \quad if \; r_i < 0 \end{cases}$$

Recalling that the form of wage function is assumed in assumption 2, then the net benefit of quitting in a private enterprise is:

$$\sigma r_i \theta_i - c$$

and an individual in a private enterprise quits if

$$r_i > \frac{c}{\sigma}$$

The ratio of quitting workers in private enterprises therefore depends on the distribution of the error term. Recalling that r_i is assumed to obey a uniform distribution[12] within

[11] The reallocation cost is caused by job market friction. Job market friction is the friction in the form of information gathering delay and turnover cost which is commonly observed (Mortensen and Pissarides, 1999). Therefore, a reallocation cost should be included in this model.
[12] The distribution itself does not influence the implications of the model and just changes the ratio of

$(-\alpha,\alpha)$, then the ratio of quitting in private enterprises is

$$\begin{cases} \frac{\alpha\sigma - c}{2\alpha\sigma} & if\ c < \alpha\sigma \\ 0 & if\ c \geq \alpha\sigma \end{cases}$$

In SOEs, the net benefit of quitting is:

$$\begin{cases} -c & if\ r_i > 0 \\ -r_i\sigma - c & if\ r_i < 0' \end{cases}$$

It is obvious that quitting always generates a negative net benefit, and as a result no workers will quit in SOEs under the model settings[13], which forms the first proposition of this study:

Proposition 1. Private enterprises have higher employee turnover than SOEs if job market friction is not extremely large, that is, $c < \alpha\sigma$. As a result, SOEs are likely to invest more in organization capital compared with their private counterparts[14].

$\alpha\sigma$ is the quitting gain from information asymmetry for individuals with the largest deviation between true ability and observed ability and c is the cost from quitting (caused by job market friction). This proposition highlights the low employee turnover in SOEs that might lead to a higher organization capital investment in SOEs than in private enterprises.

The organization capital efficiency of the remaining employees in a typical SOE,

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quitting in private enterprises. Therefore, uniform distribution is chosen for simplicity.

[13] Quitting due to personal reasons has not been accounted for because the aim of this study is to compare the difference in quitting between private enterprises and SOEs. If I follow the assumption of Greenwald (1986) by assigning the same probability of quitting due to personal reasons, it will not change the difference in quitting between the private enterprises and SOEs.

[14] The simple model does not include a component modelling how firms invest in organization because it is unlikely to provide additional information by adding a decision function with employee turnover. Therefore, a logic-based approach is used.

expressed in the form of total ability $\sum_{i \in I} \theta_i$ divided by total payment to the remaining employees $\sum_{i \in I} w_i$, is derived as follows

$$\mathrm{E}_s = \frac{\sum_{i \in I} \theta_i}{\sum_{i \in I} w_i} = \frac{\sum_{i \in I} \theta_i}{\sum_{i \in I} \sigma\theta_i + \frac{1}{4}\alpha\sigma N(I)}$$

where the subscript s denotes SOEs, $N(I)$ is a function denoting the number of workers in the index set I of remaining management workers in a firm in period two and $\frac{1}{4}\alpha\sigma N(I)$[15] is the excess payment for the remaining overvalued management workers.

The organization capital efficiency of the remaining employees in a typical private enterprise is:

$$\mathrm{E}_p = \frac{\sum_{i \in I} \theta_i}{\sum_{i \in I} w_i} = \frac{\sum_{i \in I} \theta_i}{\sum_{i \in I} \sigma\theta_i} = \frac{1}{\sigma}$$

where the subscript p denotes private enterprises. Obviously, $\mathrm{E}_s < \mathrm{E}_p$ and therefore the second proposition is summarized as follows:

Proposition 2. SOEs have lower organization capital efficiency than private enterprises, which is caused by the excess payment for the remaining overvalued[16] management workers.

Up to this point, I have not yet accounted for the lower sensitivity of earnings to performance (Yu and Egri, 2005) as well as the lower risk in SOEs due to soft budget constraints (Kornai et al., 2003) than in private enterprises, which is likely to cause less turnover of employee and less efficiency of organization capital. However, this simple

[15] Noting that half of remaining employees in a typical SOE are overvalued with an average amount of $\frac{1}{2}\alpha$.

[16] Overvalued means a worker is being paid at a rate higher than that appropriate to her/his ability.

model does provide a clue as to how the institutions in SOEs are able to lower employee turnover and impair the efficiency of their organization capital. Empirical evidence for the above propositions will be demonstrated in the sections below.

3.4 Empirical evidence from Chinese listed firms

3.4.1 Methodology

SOEs are likely to invest more in organization capital and the efficiency of organization capital in the SOEs is likely to be lower, as per the propositions in section 3. To test these propositions, one needs to first measure intensity of organization capital as well as ownership control type of a firm and then construct an interaction term between ownership control type and organization capital. The following demonstrates details on this process.

<u>Measuring intensity of organization capital.</u> There are two ways to measure organization capital intensity. The first is to use the ratio of organization capital to book assets[17] as done by Eisfeldt and Papanikolaou (2013). The second is to directly use organization capital but add the book assets as a control variable. In this study, both measurements are adopted to ensure the robustness of results.

<u>Measuring ownership control type.</u> Measurement of ownership control type is based on the proportion of state-owned shares. Traditionally, holding 20% or more of the shares is

[17] The ratio of organization capital to book asset has been winsorized at level 1% and 99% to alleviate the effects of the outliers.

viewed as being able to effectively control a firm when shares are not concentrated. Therefore, this study defines listed companies with more than 20% of shares owned by the state as SOEs. While this definition is correct in most cases, there are still some cases where a listed company is controlled by a private investor though the state-owned shares ratio is more than 20%, or a listed company is controlled by the state though the state-owned shares ratio is less than 20%. To alleviate potential worries on the threshold of defining an SOE, this study conducts sensitivity analysis by changing the threshold to either 10% or 30%[18]. Changing the threshold to 50% or more is inappropriate because most of the listed SOEs have a state share ratio less than 50%.

<u>Measurements of firm performance.</u> Three measurements that are commonly used in the financial literature are used in this study, including return of asset (ROA) and operation cash flow of asset (CFOA) and Tobin's Q. Return of asset is used to measure the profitability of a company while operation cash flow of asset is a measurement of profit quality, and Tobin's Q is a growth indicator from the perspective of the stock market. The logarithms of the above measurements are taken for the convenience of comparison[19].

<u>Control variables.</u> The main control variables are those commonly used in the financial literature, including size, leverage, and fixed industry-level characteristics as well as external shocks. Size measured by the book assets controls for the economy of scale.

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[18] Varying the threshold to 10% or 30% does not change the results. The results of the sensitivity analysis are available upon contacting the author.

[19] ROA and CFOA may have negative values if an enterprise has a loss or the revenue quality of an enterprise is poor. Taking the logarithm of ROA and CFOA means dropping all the negative and zero observations. However, the results do not change if the levels of ROA and CFOA are used.

Leverage measured by the ratio of total debts to total assets reflects the capital structure effect. Different industries may have different characteristics in organization capital intensity and therefore 159 industry dummies are added according to the level two industry classification[20] of Shanghai Stock Exchange and Shenzhen Stock Exchange. To control for potential systematic shocks, year effects are also controlled.

3.4.2 Summary statistics

Table 3 demonstrates the summary statistics for organization capital (OC), SOE dummy, book assets and leverage. This sample consists of 2,510 listed firms and an average time span of around 6 years. The amount of organization capital is significant in Chinese listed firms, with a mean of RMB 6,560,018 for the non-service group and a mean of RMB 4,305,280 for the service group. However, compared with book assets, the mean of which is RMB 7,460,000,000 for the non-service group and RMB 6,560,000,000 for the service group, the amount of organization capital is still much smaller than that of book assets. This is consistent with the production structure in China: physical capital still plays an important role in production while management is less important. In a developed economy such as the US, the median organization capital to physical capital ratio is as high as 1.079 (Eisfeldt and Papanikolaou, 2013). The possible explanation is as follows: first, the labour wage is low in a developing country compared with the costs of machines, buildings et cetera; second, China is likely to have more secondary industries than the US and therefore requires more equipment and buildings than the US. According to the mean of SOE dummy, approximately 37% of observations are classified as SOEs. The average

[20] This classification divides all the firms into 160 industries. I drop one dummy to prevent collinearity.

leverage, which is measured by the mean of debt to asset ratio, is not high, at 45% for the non-service group and at 79% for the service group. The sample in this study is generally reasonable and representative, with both sufficient observations of SOEs and private enterprises, as well as observations of generally normal leverage.

Table 3 Summary Statistics

Non-service group						
Variable		Mean	Std. Dev.	Min	Max	Observations
OC	overall	6560018	52800000	453.70	2.08E+09	N = 11082
	between		45500000	103484.20	1.55E+09	n = 1886
	within		19200000	-699000000	8.07E+08	T-bar = 5.88
SOE dummy	overall	0.36	0.48	0.00	1.00	N = 11082
	between		0.36	0.00	1.00	n = 1886
	within		0.33	-0.57	1.27	T-bar = 5.88
Book assets	overall	7.46E+09	4.92E+10	17900000	2.34E+12	N = 11082
	between		4.7E+10	153000000	1.53E+12	n = 1886
	within		1.79E+10	-5.26E+11	8.22E+11	T-bar = 5.88
Leverage	overall	0.45	1.05	0.00	96.96	N = 11082
	between		0.70	0.01	28.27	n = 1886
	within		0.82	-27.41	69.15	T-bar = 5.88
Service group						
Variable		Mean	Std. Dev.	Min	Max	Observations
OC	overall	4305280	18600000	43109.62	5.52E+08	N = 3916
	between		16100000	52870.06	3.49E+08	n = 624
	within		7932396	-220000000	2.07E+08	T-bar = 6.28
SOE dummy	overall	0.39	0.49	0.00	1.00	N = 3916
	between		0.35	0.00	1.00	n = 624
	within		0.35	-0.53	1.32	T-bar = 6.28
Book assets	overall	6.56E+09	2.13E+10	84823.6	4.79E+11	N = 3916
	between		1.57E+10	159000000	2.14E+11	n = 624
	within		1.32E+10	-1.12E+11	3.63E+11	T-bar = 6.28
Leverage	overall	0.74	14.19	0.01	877.26	N = 3916
	between		5.11	0.02	125.91	n = 624
	within		13.13	-124.72	752.09	T-bar = 6.28

Notes: SOE dummy=1 if SOE and SOE dummy=0 if private enterprise.
Source: Author's own calculation.

3.4.3 Results

<u>Organization capital investment</u>

Table 4 reports the results on differences in organization capital investment between SOEs and private enterprises. Both measurements of organization capital indicate that SOEs invest more in organization capital than private enterprises, which is consistent with proposition 1. Specifically, on average SOEs have 3% more organization capital or a 3% higher ratio of organization capital to book assets than private enterprises. When it comes to firm size, a larger size is associated with a larger amount of organization capital but with a lower ratio of organization capital to book assets. This might indicate that while larger firms need more organization capital, the relationship is concave. The reason might be that organization capital, as a type of intangible capital, can be simultaneously used in several activities (McGrattan and Prescott, 2014, 2010) and thus have an economy of scale. Leverage is positively correlated with both the absolute amount of organization capital and the ratio of organization capital to book assets. High leverage often indicates a firm is expanding and therefore the firm might require more organization capital.

Table 4 Differences in organization capital investment between private enterprises and SOEs

	(1)	(2)
VARIABLES	ln(OC)	ln(OC/K)
SOE	0.0369***	0.0334***
	(0.0140)	(0.0128)
Size	0.789***	-0.187***
	(0.00749)	(0.00560)
Leverage	0.00971***	0.00118***
	(0.00158)	(0.000332)
Constant	-2.937***	-3.436***
	(0.157)	(0.120)
Observations	14,998	14,998
R-squared	0.720	0.426
Industry FE	YES	YES
Year FE	YES	YES

Notes: Pooled OLS regression; robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's own calculation.

The efficiency of organization capital

Organization capital is embodied in key employees of a firm and thus its efficiency may be influenced by the institutions of the firm. In an SOE, due to the existence of the bianzhi system, it is difficult to demote or fire a formal employee. Moreover, because the main shareholder is the government and monitoring is relatively weak, the wage of managers is likely to be less sensitive to their performance compared with that of private enterprises, which provides fewer incentives for managers to work hard. To test whether ownership control type and its associated institutions influence the efficiency of organization capital, an interaction term between the logarithm of organization capital to book assets and a SOE dummy is incorporated into the model specifications.

First, the role of organization capital in three performance measurements of listed firms is tested. According to (1), (2) and (3) in Table 5, an increase in the ratio of organization capital to book assets significantly improves firm performance. On average, a 10% increase in the organization capital book assets ratio is predicted to increase 1.67% in CFOA, 1.1% in ROA and 1.4% in Tobin's Q.

Second, the efficiency difference in organization capital of different ownership control types is tested. The interaction term is negative across (4), (5) and (6) and is significant in (4) and (5), which provides some evidence on proposition 2 that the efficiency of organization capital is lower in SOEs compared with that of private enterprises in China. On average, a 10% increase in the ratio of organization capital to book assets is correlated with a 1.04% increase in CFOA for SOE and a 2.07% increase in CFOA for private enterprises; a 10% increase in the ratio of organization capital to book assets is correlated with a 0.824% increase in ROA for SOE and a 1.28% increase in ROA for private enterprises; a 10% increase in the ratio of organization capital to book assets is correlated with a 1.28% increase in Tobin's Q for SOEs and a 1.47% increase in Tobin's Q for private enterprises.

The property rights theory of firms suggests that SOEs should perform less efficiently and profitably than private enterprises (Alchian, 1965). Although in some research SOEs have better performance than private enterprises because of the limited competition due to regulation in some industries, SOEs do perform worse than private enterprises under a competitive environment (Boardman and Vining, 1989). Unsurprisingly, Chinese SOEs are not an exception. On average SOEs perform worse than private enterprises after controlling for industry and year effects. The lower efficiency in organization capital is likely to be one of the contributors to the worse performance of SOEs than private enterprises. Therefore, it is necessary to deepen SOE reforms in China to improve the efficiency of Chinese SOEs.

Table 5 The role of organization capital in firm performance in the context of different ownership

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Ln(CFOA)	Ln(ROA)	Ln(Tobin's Q)	Ln(CFOA)	Ln(ROA)	Ln(Tobin's Q)
Ln(OC/K)	0.167***	0.110***	0.140***	0.207***	0.128***	0.147***
	(0.0161)	(0.0124)	(0.00819)	(0.0189)	(0.0149)	(0.0101)
Ln(OC/K) *SOE				-0.103***	-0.0456**	-0.0186
				(0.0244)	(0.0207)	(0.0123)
SOE				-0.736***	-0.361**	-0.153*
				(0.176)	(0.154)	(0.0894)
Size	0.0657***	0.139***	0.181***	0.0660***	0.141***	0.183***

	(0.0104)	(0.0199)	(0.00695)	(0.0105)	(0.0204)	(0.00693)
Leverage	0.000303	-1.736***	0.0141***	0.000425	-1.734***	0.0141***
	(0.000794)	(0.220)	(0.00421)	(0.000820)	(0.221)	(0.00421)
Constant	-3.664***	-4.824***	-3.209***	-3.379***	-4.451***	-3.173***
	(0.230)	(0.346)	(0.144)	(0.246)	(0.398)	(0.156)
Observations	11,366	13,308	14,998	11,366	13,308	14,998
R-squared	0.087	0.179	0.314	0.088	0.179	0.314
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Pooled OLS regression; robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Author's own calculation.

3.5 Conclusions and policy implications

Physical capital is unlikely to be affected by institutions because, regardless of institutions, machines and equipment are likely to run the way they are designed. However, organization capital, which is capital embodied in the key employees of a firm, is likely to be affected by institutions. The prevalence of SOEs in China provides a rare opportunity for testing the role of institutions in investment and efficiency of organization capital. Based on data from Chinese listed firms, this study confirms the importance of organization capital as a production factor in China based on consistent evidence from OLS, fixed effects and the Levinsohn-Petrin (2003) models. Service is likely to rely more on organization capital than non-service. The coefficients of organization capital in the production function are close to those of Tronconi and Marzetti (2011) but the ratio of organization capital to book assets is much smaller in China.

A simple theoretical model capturing some important characteristics of the human resource management practice in SOEs is constructed in this study to discuss the source of low employee turnover and low efficiency of organization capital in SOEs. Demoting or firing a formal employee is difficult in SOEs and therefore the wage of employees cannot be adjusted to reflect their true ability when they demonstrate ability lower than expected. The model argues that excess payments to employees whose ability is previously overestimated are one of the reasons that SOEs have relatively low employee turnover and relatively low organization capital efficiency.

The empirical evidence is consistent with the predictions of the simple model. SOEs, on average, have around 3.5% more organization capital compared with private enterprises, which is likely to be a result of the relatively low employee turnover in SOEs. The result is robust across two measurements of organization capital: the level of organization capital and the ratio of organization capital to book assets, after controlling for size, leverage, industry and year effects. The difference in organization capital efficiency is also significant. SOEs on average have lower organization capital efficiency than private enterprises. The difference is robust across three key measurements of firm performance: CFOA (operation cash flow of asset), ROA (return of asset) and Tobin’s Q.

This study provides an important basis for policies promoting organization investment in China. Organization capital has become an important production factor for China according to the results of this study, and a further increase in productivity requires further investment in organization capital. Moreover, this study reveals the importance of continuing reforms in SOEs of China. The efficiency of organization capital is relatively low in SOEs because human resource management practice is inflexible and external effective supervision is relatively weak. According to Zhang (2006), managers of SOEs are selected and reviewed by bureaucrats instead of capitalists, which indicates relatively weak supervision from the bureaucrats because the bureaucrats do not own the capital of the SOEs. To improve the efficiency of organization capital in SOEs, the wage system and human resource administration system in SOEs should be more flexible and marketized, which would aim to reduce excess payments to employees as well as to provide more incentives for management to work hard. Specifically, the current bianzhi system in SOEs should be eliminated and contract-based employment should dominate. Once the bianzhi system is extinguished, direct interventions from the government and inflexibility in human resource management is minimized because the key employees in SOEs will no longer be parts of the bureaucratic system. Then firms can adjust excess payments to previously overpaid employees more easily. Moreover, further privatization is needed to allow private power to be involved in the corporate governance of SOEs. For instance, top managers of SOEs should be selected via the professional manager market instead of through appointment from the government. With supervision from private power, the efficiency of organization capital in SOEs is also likely to increase.

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4. Intangible capital and sectoral energy intensity: Evidence from 40 economies between 1995—2007*

Intangible capital has been found to be an increasingly important source of productivity and economic growth. However, its effects on energy intensity have received little attention. Given the importance of reducing energy intensity, this study advances the understanding of the relationship between intangible capital and sectoral energy intensity by taking advantage of a rich dataset of 40 economies derived from the World Input-Output Database (WIOD), spanning across 13 years (1995 – 2007). A relatively robust causal relationship between intangible capital and sectoral energy intensity has been identified. The qualitative and quantitative interactions of this relationship with income level and sectoral heterogeneity have also been revealed. It is found that the effect of intangible capital in reducing sectoral energy intensity generally diminishes along with increasing income level but moderate quadratic relationship is identified in some types of intangible capital. Finally, sectors where intangible capital has the largest and smallest effect are also pinpointed.

4.1 Introduction

Intangible capital has been identified to have significant impacts on economic activities. Intangible capital is often defined as the immaterial resources that enter the production process and are of importance for the creation of new products as well as the improvement of existing products and the production process. Examples of intangible capital include research and development (R&D) investment, advertising (brand equity),

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* This chapter has also been published in *Energy Policy*.

organization capital, staff training, technology licences, patents, and copyrights (Corrado et al. 2013). Numerous economists have devoted much effort to measuring it as well as evaluating its role from various perspectives, including studies on intangible capital as a source of growth in different economies at both national and sectoral level (e.g. van Ark et al. 2009; Corrado and Hulten 2010; Chun and Nadiri 2016), discussion on the role of intangible capital in firms' valuation and productivity (e.g. Atkeson and Kehoe 2005; Arato and Yamada 2012; Eisfeldt and Papanikolaou 2013; Gourio and Rudanko 2014) and adding intangible capital to solve macroeconomic puzzles (e.g. McGrattan and Prescott 2010; Borgo et al. 2013; Gourio and Rudanko 2014a).

While the economic effect of intangible capital has been well documented, its environmental counterpart has received little attention. One important environmental dimension is the change in energy intensity, or energy efficiency, associated with the increasing use of intangible capital. Energy intensity remains a concern of climate change and environmental scientists due to the fact that economic activities still primarily rely on fossil fuels (Wang et al. 2011; Zhang and Da 2015). Although renewable energy is growing over time, it is unlikely to take a leading role in the near future when facing the increasing energy demand. World energy consumption is forecast to increase by 48% by 2040 and fossil fuels are likely to still account for more than 3/4 of the world energy consumption by then (U.S. Energy Information Administration, 2016). Air pollution from the consumption of fossil fuels has been an increasing health concern: it is now the fourth greatest risk factor for human health worldwide (International Energy Agency, 2016).

Energy efficiency (EE), often measured by energy intensity, is a cost-effective way to decouple economic growth from energy demand and its associated carbon emissions and other pollutions. Energy efficiency is regarded as a key policy to reconcile the increasing tension between economic growth and climate change mitigation around the world (Han et al., 2018). Decreasing energy intensity is a direct method to decouple economic growth from energy consumption and associated carbon emissions (Proskuryakova and Kovalev, 2015). Reducing energy intensity is also considered to be an effective approach to mitigating climate change, addressing peak oil and improving energy security (Sadorsky, 2013). The European Union (EU) has made energy intensity a key pillar of its climate change strategy (Löschel et al., 2015). Furthermore, the decline in sectoral energy intensity is found to be a major driver of the decline in aggregate energy intensity (Greening et al. 1997; Ma and Stern 2008; Sue Wing 2008; Voigt et al. 2014; Wang and Wei 2016), which indicates that it is important to study the factors that drive the dynamic of sectoral energy intensity.

Although the role of intangible capital in economic and productivity growth has been widely discussed in the existing literature, a causal relationship between intangible capital and sectoral energy intensity has not yet been established. The literature often focuses on the role of R&D (Fisher-Vanden et al., 2004; Herrerias et al., 2016; Newell et al., 1999) but neglects the roles of other types of intangible capital in energy efficiency improvement. Furthermore, the heterogeneous effects of intangible capital on sectoral energy intensity in various sectors and economies of different development stages remain unknown.

This study aims to advance the knowledge of the role of intangible capital in affecting energy intensity by taking advantage of a rich worldwide dataset from the World Input-Output Database (WIOD) developed within the 7th Framework Programme of the European Commission and providing a much more comprehensive analysis on the role of intangible capital in sectoral energy intensity.

This study is important for both academic and policy areas. This study will advance the knowledge on the relationship between intangible capital and energy intensity and the heterogeneous effects of intangible capital on sectoral energy intensity across economies of different development stages as well as various sectors. The study is also useful to policy makers for better understanding the heterogeneous role of intangible capital in various economies and sectors. For example, this study will inform the industry and policy makers of a few new channels for reducing energy intensity in addition to R&D investment. The role of intangible capital in improving energy efficiency among countries at different development levels also can inform the global efforts on narrowing development gap (Sheng and Shi, 2013) and achieving the UN goals of Sustainable Energy for All. Pinpointing sectors can also suggest priority areas for investing in intangible capital across sectors for the purpose of reducing energy intensity.

The contributions of this paper are fourfold. First, it constructs a large sectoral dataset of intangible capital across 40 economies that is suitable for econometric analysis for future studies. Second, it innovatively establishes a theoretical causal relationship between intangible capital and sectoral energy intensity. Third, it provides new knowledge on the heterogeneous effects of intangible capital on sectoral energy intensity, which might generate important information for policy analysis. Analysis by sector and by economy is conducted to reveal how the effects of intangible capital vary in different sectors as well as at different development stages. Fourth, the effects of income on the reduction effect of intangible capital on sectoral energy intensity are identified.

This essay is organized as follows: the next section describes the definition and measurement of sectoral energy intensity and intangible investment; section 3 discusses the theoretical linkage between intangible capital and sectoral energy intensity; section 4 depicts the data and methodology; section 5 explains the empirical results; section 6 draws the conclusion.

4.2 Measuring sectoral energy intensity and intangible capital

4.2.1 Sectoral energy intensity

Two definitions of sectoral energy intensity co-exist in the literature: one is energy use divided by sectoral value added and the other is energy use denominated by sectoral gross output. Both methods have theoretical basis, and their uses depend on the method of decomposition applied. If aggregate energy intensity is decomposed using index decomposition analysis (IDA), then we have the following:

$$I = \frac{E}{Y} = \sum_i \frac{Y_i}{Y}\frac{E_i}{Y_i} = \sum_i S_i I_i$$

I is the aggregate energy intensity in an economy of which the definition is aggregate energy use *E* divided by gross domestic product (GDP) *Y* of the economy. Y_i is the value added of sector i, E_i is the energy use of sector *I*, and S_i is the share of sector *i* in the aggregate economy. Obviously, the energy intensity of sector *i*, I_i, in this context should be defined as sectoral energy use divided by sectoral value added to avoid the double counting problem found with the other definition.

If the aggregate energy intensity is decomposed using the structural decomposition analysis (SDA), then we have the following[1]:

$$E = \hat{\varepsilon}(\mathrm{I} - \mathrm{A})^{-1}\hat{y}$$

E is the aggregate energy use; $\hat{\varepsilon}$ is a diagonal matrix of energy intensity in different sectors; $(\mathrm{I} - \mathrm{A})^{-1}$ is the Leontief inverse; $\hat{y}$ is a diagonal matrix of the final demand. In this case, sectoral energy intensity is defined as sectoral energy use divided by sectoral gross output.

In this study, the definition of energy intensity comes from the IDA method, that is, sectoral energy use divided by sectoral value added. The use of this definition is common in the existing literature (Zhang 2003; Ma and Stern 2008; Mulder and de Groot 2012; Wu 2012). The measurement of sectoral energy use is derived from the World Environmental Account in the WIOD. The sectoral energy use data in the WIOD is aggregated across 26 energy carriers and is measured in physical units (TJ). The sectoral value added is acquired from the World Supply and Use Tables in WIOD,

[1] For the derivation of the SDA equation, please see appendix A.

which will be deflated to 1995 constant USD[2].

4.2.2 Intangible capital

In the recent two decades, increasing effort has been devoted to finding suitable measures for intangible capital. Two common measures are currently being used. One is based on aggregate estimates derived from firm expenditures on 'intangibles' such as R&D, advertising and innovation (Corrado et al., 2009) while the other is mainly based on the reported intangible assets in firms' balance sheets (Marrocu et al., 2012). The empirical evidence in both cases is unanimous in pointing at intangible capital as a key element in the modern knowledge economy. When it comes to intangible capital at sectoral level, it is more appropriate to adopt an expenditure-based approach and therefore this study follows the approach of Corrado et al. (2009).

To estimate intangible capital stock, the first step is to measure the flow of intangible investment. Three types of intangible expenditure defined by Corrado et al. (2009) are derived from the intermediate statistics from the supply and use tables within the WIOD, which is summarized in Table 1. The accumulation of intangible capital follows the standard perpetual inventory method:

$$\mathrm{IC}_{s,t} = \mathrm{IC}_{s,t-1}(1-\delta_s) + IN_{s,t}$$

where IC refers to intangible capital; the subscripts *s* and *t* respectively denote intangible capital *s* and time; δ refers to depreciation rate; IN is intangible investment. To implement the law of motion of intangible capital, an initial value must

[2] The deflation method used will be introduced in section 4.1.

be chosen, which is according to

$$\mathrm{IC}_{s,0} = \frac{IN_{s,0}}{g_s + \delta_s}$$

where g_s is chosen to match the average real growth rate of the intangible investment s in a sector.

Table 1 Measurement and depreciation rate of intangible investment

Intangible investment	Method	Depreciation rate[3]
Computerized information	Distribute the aggregate gross fixed investment in computerized information according to the use of 'computer and related services' intermediate	0.33
Innovative property	Use 'research and development services' intermediate adjusted by the outsourcing ratio	0.2
Economic competency		
Brand equity (advertising)	Use 60%[4] of 'other business activities'[5] adjusted by the outsourcing ratio	0.6
Organization capital and staff training[6]	Use 'education services' intermediate adjusted by the outsourcing ratio	0.4

Notes: Outsourcing ratio is defined as the ratio of the value added to total intermediates. The reason why the intermediates statistics should be adjusted by the outsourcing ratio is that in the supply and use tables only outsourced intangible expenditure is counted, and directly using the intermediate statistics omits the internally produced intangible expenditure.
Source: Authors' own construction.

Following Eisfeldt and Papanikolaou (2013), the intangible capital IC is scaled by the real capital stock of a sector to alleviate possible estimation bias caused by productivity shocks, and the observations with zero intangible capital are dropped. Using the amount of tangible capital as the denominator for intangible capital also has the advantage of controlling for the size of a sector. Compared with the national level measurement of Corrado et al. (2009) and the literature following it, this measurement might be of lower

[3] The depreciation rate follows Corrado et al. (2009).
[4] Corrado et al. (2009) estimate 60% of the advertising expenditure should be capitalized
[5] 'Other business activities' includes advertising as well as market research expenditure.
[6] Organization capital and staff training refers to firm-specific human and structural resources (Corrado et al. 2009), which can be indicated by the education expenditure of firms.

accuracy. The source of inaccuracy might be caused by the deviation of the measured outsourcing ratio from the actual outsourcing ratio, ‘other business activities’ intermediates including expenditure that is not intangible investment, the distribution of computerized information investment across sectors inconsistent with that of ‘computer and related services’ intermediate etc. However, since the econometrics approach used in this study has some tolerance of measurement error, the constructed dataset should satisfy the analysis requirements[7].

4.3 Intangible capital and energy intensity: A theoretical analysis

Intangible capital, including innovations, could have significant effects on energy intensity reduction, or energy efficiency improvement. The role of innovations in energy intensity reduction has been well documented in the literature (Fisher-Vanden et al., 2004; Herrerias et al., 2016; Newell et al., 1999). Hao and van Ark (2013), in their preliminary study on the correlation between intangible investment and sectoral energy intensity using data from nine developed European economies, argued that intangible investment can promote technical change, and innovations in energy conservation as well as less use of tangible capital that accounts for the largest proportion of energy consumption in production, thus reducing energy intensity.

However, the theoretical relationship between other components of the intangible capital and energy intensity has not been discussed. Pricing power, improved operational efficiency resulting from organization capital and staff training and

[7] If the measurement error is randomly distributed, it will not cause bias in the estimation results; if the measurement error is sector-specific, then it will be eliminated by the sector specific intercept.

computerized information can also exert significant impacts on lowering sectoral energy intensity and then air pollutant and carbon emissions. Motivated by the fact that intangible capital is a key production factor used by firms, this study proposes a simple theoretical analysis of the relationship between intangible capital and energy intensity. Before proceeding, energy intensity is defined as follows:

$$\mathrm{I}_{i,j,t} = \frac{E_{i,j,t}}{\mathrm{Y}_{i,j,t}} \tag{1}$$

where $\mathrm{I}_{i,j,t}$ refers to the energy intensity of sector i in country (economy) j at time t; E_{ij} is the energy use of sector i in country j; Y_{ij} is the value added of sector i in country j. That is, energy intensity is defined as the ratio of energy use to value added, which has been discussed in detail in section 2.

Next, a production function based on the value added method is assumed as follows:

$$\mathrm{Y}_{i,j,t} = A_{i,j,t}F_i(L_{i,j,t}, K_{i,j,t}, IC_{i,j,t}) \tag{2}$$

where $A_{i,j,t}$ is the productivity of sector i in country j at time t; L, K, IC are respectively the labour input, tangible capital input and intangible capital input of sector i in country j; $F_i(L_{i,j,t}, K_{i,j,t}, IC_{i,j,t})$ is the production function of sector i. Using value added as output and labour and capital as inputs at sectoral level is common in the existing literature and therefore well founded (Wei et al., 2007).

Moreover, assume that using intangible capital does not consume extra energy, which is consistent with the nature of intangible capital[8]. Therefore, we have the relationship between intangible capital and sectoral level energy intensity based on equations (1) and

[8] For example, using new design, R&D knowledge or new management practices does not consume energy. It is the tangible capital such as equipment and buildings that consume energy.

(2) as follows:

$$\frac{\partial(\frac{E_{i,j,t}}{Y_{i,j,t}})}{\partial IC_{i,j,t}} = -\frac{E_{i,j,t}}{{Y_{i,j,t}}^2} A_{i,j,t} \frac{\partial F_i(L_{i,j,t}, K_{i,j,t}, IC_{i,j,t})}{\partial IC_{i,j,t}} < 0 \tag{3}$$

Equation (3) is the derivative of energy intensity with respect to intangible capital, which is negative. This indicates that an increase in intangible capital can lower sectoral energy intensity. The mechanism is intuitive: the increasing use of intangible capital increases the value added given other inputs remain constant but does not increase energy use, and therefore lower the energy intensity.

Theoretically, intangible capital might have two channels to increase value added assuming constant other inputs. One is through increasing pricing power and then value added per unit of product. Not only product creation / improvement R&D but also brand equity is often found to be associated with the pricing power of firms and then value added per unit of products (Corrado et al., 2005; Jones and Williams, 2000). Since R&D as a source of pricing power has been well regarded, the following illustration mainly focuses on the brand equity. Brand equity is often found to create a price premium for a product. Advertising itself can alter the preference of consumers: they may perceive a well-advertised product with distinctive packaging as being of high quality. Specifically, Klein and Leffler (1981) argue that consumers often use advertising intensity as an indicator of quality. Kirmani and Wright (1989) then provide empirical evidence for this proposition, showing that consumers do perceive products with high advertising expenditure as of high quality and are therefore willing to pay a price premium.

The other channel is through improving production efficiency and then increasing the units produced given constant resource input. R&D, organization capital and software are found to enhance the production process and then the production efficiency (Corrado et al., 2005). Examples include new production protocols, and advanced management practice as well as well trained workers.

In sections 4 and 5, we will test the empirical relationship between intangible capital and energy intensity. It is worth noting that this study works beyond establishing a causal relationship between intangible capital and sectoral energy intensity – heterogeneity in this relationship as well as the heterogeneous impacts of income level on sectoral energy intensity across economies and sectors are also examined.

4.4 Data source and empirical strategy

A dataset of intangible capital for 40 economies across 34 sectors from 1995 to 2007[9] is constructed based on data retrieved from the WIOD and the capitalization criteria for intangible capital of Corrado et al. (2009), which provides a solid basis for an insightful analysis of the heterogeneous impacts of intangible capital and economic development on sectoral energy intensity. Basic fixed effects regressions are then used to provide an overall picture of the roles of various intangible capital across service and non-service sectors and economies of high income and low income. The system GMM method is further utilized to establish a relatively robust causal relationship. Finally, multilevel regressions are conducted to identify the quantitative heterogeneity in the impacts of

[9] The sector-specific deflator, which is derived from the supply and use tables in previous year price, is only available from 1995 to 2007.

various intangible capital on sectoral energy intensity.

4.4.1 The WIOD and the Penn World Table 8.1

The WIOD is built on national accounts data that was developed within the 7th Framework Programme of the European Commission. The WIOD database has two main advantages compared with previously available data sources. First, throughout the data collection efforts, harmonization procedures were applied to ensure international comparability of the data. This ensures data quality and minimizes the risk of measurement errors. Second, the WIOD includes sectoral price deflators, the use of which allows one to retain important information and the heterogeneity of the sectors with respect to price dynamics. This represents an improvement over the use of aggregate national price deflators. A complete list of the 34 sectors included in the database is shown in Appendix B.

The intangible capital data is derived from the supply and use tables within the WIOD; the energy use data is obtained from the World Environmental Account. Real tangible capital stock at 1995 constant price is obtained from the Social Economic Account and is converted to 1995 constant USD. The Penn World Table 8.1 provides the data of GDP per capita (see Feenstra et al. (2015) for more detailed discussion). All data from the Penn World Table 8.1 is converted to 1995 constant USD based on the national price level and 1995 USD exchange rate.

4.4.2 Empirical strategy

The key variables of interest in this study are the intangible-tangible ratio and the income level of an economy. To provide an overall picture of the heterogeneous impacts of intangible capital on sectoral energy intensity, several interaction terms and control variables are introduced. That is, an empirical model is assumed as follows

$$I_{i,j,t} = \beta_1 \frac{IC_{s,i,j,t}}{TC_{i,j,t}} + \beta_2 \frac{IC_{s,i,j,t}}{TC_{i,j,t}} \times low\_income + \beta_3 \frac{IC_{s,i,j,t}}{TC_{i,j,t}} \times service + \beta_4 gdp_{pc_{j,t}} \times low\_income + \beta_5 gdp_{pc_{j,t}} \times service + \beta_6 gdp_{j,t} + \beta_7 time_t + \alpha + \varepsilon_{i,j,t}, \qquad (4)$$

where I is sectoral energy intensity, *IC* is intangible capital and *TC* is tangible capital. The subscript *s* represents intangible capital *s*; *i, j, t* respectively stand for sector *i*, country *j* and time *t*; gdp deonotes the aggregate GDP of an economy, which is used to control for economy size; *time* refers to time fixed effects. α is the intercept and $\varepsilon_{i,j,t}$ is the error term. low_income indicates whether an economy is low income or not, the classification of which follows that of the World Bank[10]. $service$ denotes whether a sector is a service sector or not, the classification of which is demonstrated in Appendix B. $time_t$ is the year dummy, which controls for fluctuation in energy price as well as worldwide shocks. All variables are in the form of logarithm except for the dummy variables.

To eliminate the possible estimation bias, we introduce the system GMM method. Although endogeneity is unlikely to be present in this case given that relevant variables, time fixed effects and individual sectoral fixed effects are controlled for, it is still possible that there are some unobservable factors that simultaneously affect the sectoral energy intensity and the intangible capital to tangible capital ratio and thus undermines the causal effects proposed in this study. For instance, some economy or sector-specific

[10] Please see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519.

environmental policies might influence both the energy intensity and the intangible capital ratio; an increase in sectoral productivity might simultaneously decrease the sectoral energy intensity and change the intangible tangible ratio subject to the production structure of a sector. System GMM uses both lagged differenced variables and lagged variables as instruments, which can partially solve the endogeneity problems. Compared with differenced GMM, the system GMM method has better estimation efficiency because it additionally assumes that the first differences of instrumental variables are uncorrelated with the fixed effects, which allows the introduction of more instruments and therefore improves estimation efficiency dramatically (Roodman, 2009). To test the validity of the instruments as well as the additional assumption on which system GMM is based, the Hansen (1982) J test and the Arellano-Bond test will be conducted.

To further analyse the impacts of intangible capital across economies of different income levels and various sectors, multilevel analysis is then conducted. Multilevel analysis provides economy and sector-specific coefficients for variables of interest, which forms the basis of a more detailed study on the heterogeneous effects of intangible capital on sectoral energy intensity. Specifically, a two-level hierarchy structure is identified: the first is the economy level while the second is the sector level. The coefficient of a specific sector therefore consists of three components: the worldwide average, the deviation due to the economy it belongs to and the deviation caused by sector-specific factors. Additional regressions will also be conducted to study the quantitative interactions between the economy and sector-specific coefficients and the income levels.

4.4.3 Descriptive analysis

The features of the dataset used in this study are summarized in Table 2. It consists of 605 sectors from 40 economies across approximately 12 years with more than 7,000 observations in total. The heterogeneity of GDP per capita and aggregate GDP indicates that the sample covers economies of different income levels and scales. The variation of production structure can also be seen from the large standard deviations of the various intangible-tangible ratios.

Table 2 Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
log(energy intensity)	overall	1.76	1.76	-7.42	11.99	N = 7662
	between		1.66	-2.70	8.32	n = 637
	within		0.64	-2.95	6.57	T-bar = 12.03
log(Intangible/Tangible)	overall	-2.69	2.08	-13.06	10.79	N = 7662
	between		1.82	-10.14	6.25	n = 637
	within		1.03	-16.21	6.82	T-bar = 12.03
log(RD/Tangible)	overall	-5.48	2.39	-17.90	10.78	N = 7332
	between		2.20	-12.34	5.89	n = 612
	within		0.94	-27.19	-0.58	T-bar = 12.00
log(CI/Tangible)	overall	-3.97	2.36	-17.97	10.23	N = 7104
	between		2.08	-9.82	5.78	n = 588
	within		1.13	-15.86	5.69	T-bar = 12.08
log(BE/Tangible)	overall	-3.92	1.62	-13.70	4.40	N = 7377
	between		1.45	-10.99	1.57	n = 614
	within		0.74	-13.88	2.04	T-bar = 12.01
log(OC&ST/Tangible)	overall	-6.33	1.82	-15.74	3.00	N = 7406
	between		1.67	-12.72	-0.29	n = 620
	within		0.72	-21.78	-2.79	T-bar = 11.95
log(GDP per capita)	overall	2.47	1.14	-0.96	4.36	N = 7662
	between		1.14	-0.73	4.16	n = 637
	within		0.14	1.97	3.04	T-bar = 12.03
log(GDP)	overall	12.09	1.68	8.18	16.19	N = 7662
	between		1.67	8.38	16.04	n = 637
	within		0.15	11.54	12.70	T-bar = 12.03

Notes: The unit of GDP per capita is thousand 1995 USD; the unit of GDP is million 1995 USD; the unit of energy intensity is trillion joules (TJ) per million 1995 USD.

Source: Authors' own calculation.

To illustrate the overall relationship between intangible capital and sectoral energy intensity, scatter plots and best fitting lines are drawn for the overall intangible tangible ratio as well as its various categories (please see Figure 1, sectoral fixed effects have been controlled). Significant negative relationship can be easily seen in all of the subfigures with varying slopes. However, the correlation itself is not causal relationship and the heterogeneous impacts of intangible capital on sectoral energy intensity still remain unclear. The next section will further discuss these issues.

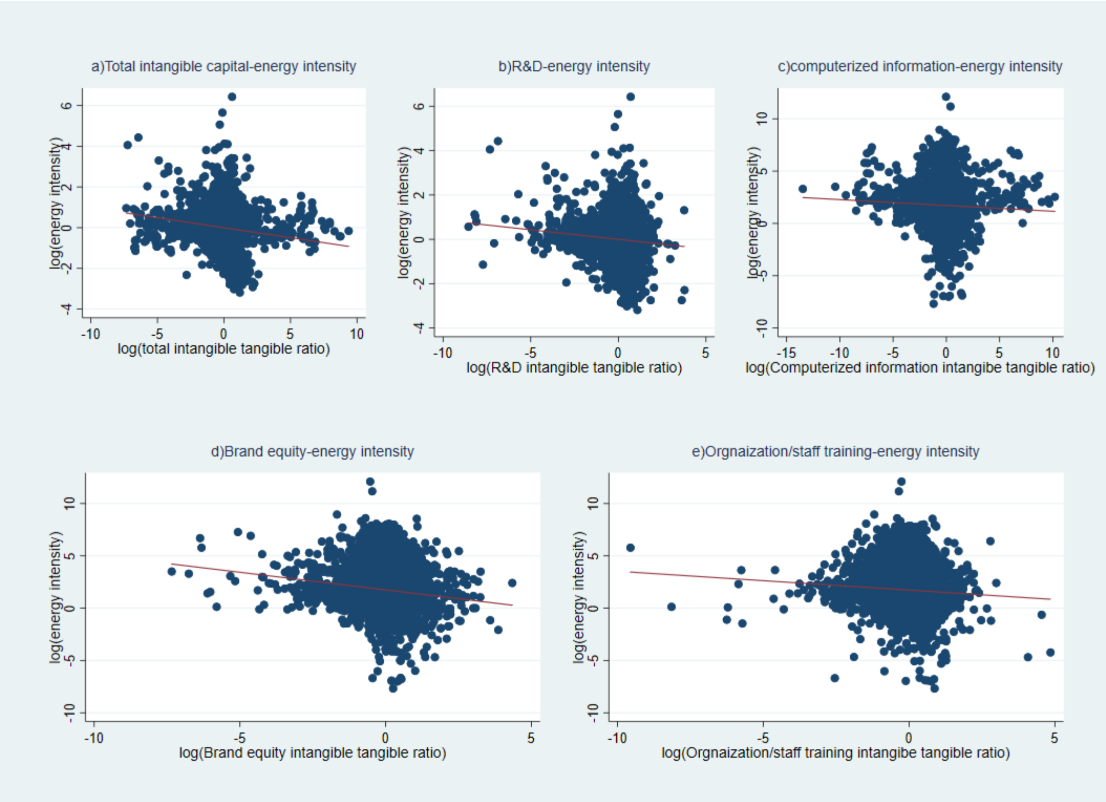


Figure 1 Scatter plots of the relationship between intangible capital and sectoral energy intensity (sectoral fixed effects controlled)
Source: Authors' own calculation.

4.5 Empirical results

4.5.1 An overall picture

Table 3 demonstrates the heterogeneous impacts of intangible capital and income level on sectoral energy intensity. The negative relationship between intangible capital, income level and sectoral energy intensity can be clearly seen. When controlling for income level and intangible-tangible ratio, the larger the economy a sector belongs to, the less energy efficient the sector is, which might be caused by the diseconomy of scale.

The overall intangible capital and its four major components have consistent impacts on energy intensity. On average, a 1% increase in overall intangible-tangible ratio leads to a 0.09% decline in sectoral energy intensity; a 1% increase in R&D tangible ratio leads to a 0.10% decrease in sectoral energy intensity; a 1% increase in computerized information (CI) tangible ratio leads to a 0.05% drop in sectoral energy intensity; a 1% increase in brand equity (BE) causes 0.29% reduction in sectoral energy intensity; a 1% rise in organization capital and staff training (OC&ST) leads to a 0.176% decrease in sectoral energy intensity.

In respect of the role of income level, a 1% increase in GDP per capita generally leads to an approximately 5% decrease in sectoral energy intensity. When it comes to the heterogeneous effects across service and non-service sectors as well as high, and low and middle income economies, it is found that the impacts of intangible capital and income level in reducing sectoral energy intensity are larger in service sectors and low and middle income economies. For the impacts of intangible capital, the differences can be as large as 10 times and as small as 10%. As for the impacts of income level, the difference is much smaller.

Table 3 Heterogenous impacts of intangible capital and income level on sectoral energy intensity (Fixed effects)

	Fixed effects									
Sectoral energy intensity	All Intangible		R&D		CI		BE		OC&ST	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intangible	-0.0923***	-0.0275**	-0.104***	-0.0459***	-0.0517***	-0.00559	-0.294***	-0.219***	-0.176***	-0.148***
	(0.0169)	(0.0128)	(0.0152)	(0.0147)	(0.0127)	(0.00879)	(0.0267)	(0.0305)	(0.0181)	(0.0164)
Intangible×service		-0.0669***		-0.128***		-0.0287*		-0.0361		-0.0728***
		(0.0249)		(0.0346)		(0.0147)		(0.0460)		(0.0110)
Intangible×low income		-0.200***		-0.0528		-0.171***		-0.114**		-2.807
		(0.0418)		(0.0693)		(0.0351)		(0.0495)		(2.537)
GDP pc	-5.460***	-4.801***	-6.748***	-5.875***	-5.943***	-4.555***	-5.846***	-5.137***	-5.553***	-4.985***
	(0.731)	(0.603)	(0.762)	(0.642)	(0.776)	(0.599)	(0.696)	(0.582)	(0.736)	(0.628)
GDP pc×service		-0.0777		-0.0757		-0.0238		-0.0634		-0.0708
		(0.163)		(0.166)		(0.144)		(0.153)		(0.167)
GDP pc×low income		-2.274***		-2.190***		-3.495***		-2.045***		-2.202***
		(0.316)		(0.323)		(0.421)		(0.284)		(0.335)
GDP	4.914***	4.969***	6.143***	5.964***	5.441***	4.287***	5.196***	5.139***	4.938***	5.090***
	(0.773)	(0.681)	(0.805)	(0.726)	(0.838)	(0.661)	(0.734)	(0.655)	(0.776)	(0.707)
Constant	-44.64***	-46.77***	-56.02***	-55.78***	-48.70***	-38.19***	-47.25***	-48.14***	-45.18***	-48.15***
	(7.603)	(6.828)	(7.855)	(7.224)	(8.138)	(6.461)	(7.167)	(6.521)	(7.593)	(7.063)
Observations	7,288	7,288	6,899	6,899	6,796	6,796	7,035	7,035	7,090	7,090
R-squared	0.233	0.296	0.235	0.287	0.211	0.282	0.327	0.367	0.244	0.288
Number of id	603	603	576	576	562	562	586	586	594	594
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. CI denotes computerized information; BE stands for brand equity; OC&ST indicates organization capital and staff training.

Source: Authors' own calculation.

To establish relatively robust causality between intangible capital and sectoral energy intensity, the system GMM method is adopted to eliminate the possible endogeneity. Relevant results are revealed in Table 4. Compared with the fixed effects regressions, the negative relationship between intangible capital, its major components and energy intensity remains robust with a small decline in scale. Specifically, a 1% rise in overall intangible-tangible ratio is predicted to improve sectoral energy intensity by 0.02%; a 1% increase in R&D tangible ratio on average reduces sectoral energy intensity by 0.09%; a 1% growth in computerized information tangible ratio generally leads to a 0.005% drop in sectoral energy intensity; a 1% rise in brand equity tangible ratio is predicted to decrease energy intensity by 0.25%; a 1% increase in organization capital and staff training tangible ratio on average causes a 0.17% decline in sectoral energy intensity. As for the impacts of income level, due to the collinearity caused by using lagged and differenced income level as instruments, in many cases it becomes insignificant or positive. The coefficients of aggregate GDP also become insignificant. The results from the system GMM regressions are an improvement on earlier studies (Hao and van Ark, 2013): they evidence a causal relationship between intangible capital and sectoral energy intensity. However, the outcomes demonstrated above only compare the impacts of intangible capital and income level across different groups. The next section will have a deeper look at this rich dataset by carrying out additional analysis.

Table 4 Heterogenous impacts of intangible capital and income level on sectoral energy intensity (system GMM)

	system GMM									
Sectoral energy intensity	All Intangible		R&D		CI		BE		OC&ST	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intangible	-0.0248*	-0.0153	-0.0809**	-0.0838***	-0.00451	-0.00722	-0.252***	-0.154***	-0.168***	-0.349***
	(0.0133)	(0.0108)	(0.0330)	(0.0279)	(0.0144)	(0.0102)	(0.0420)	(0.0432)	(0.0505)	(0.00509)
Intangible×service		-0.0889***		-0.141***		0.00518		-0.0464		-0.0825***
		(0.0219)		(0.0233)		(0.0140)		(0.0348)		(0.000707)
Intangible×low income		-0.0888***		-0.0200		0.0244		0.00295		0.0799
		(0.0343)		(0.0261)		(0.0162)		(0.0456)		(0.135)
GDP pc	0.0191	0.124	-0.238***	-0.217***	-0.153*	-0.00224	0.0376	0.156**	0.00809	0.0983*
	(0.0797)	(0.0830)	(0.0851)	(0.0635)	(0.0928)	(0.0729)	(0.0999)	(0.0717)	(0.104)	(0.0572)
GDP pc×service		-0.350***		-0.271***		-0.275***		-0.249***		-0.276***
		(0.0531)		(0.0564)		(0.0465)		(0.0842)		(0.0348)
GDP pc×low income		0.306**		-0.740***		-0.107		-0.215**		-0.536***
		(0.145)		(0.0757)		(0.144)		(0.109)		(0.0537)
GDP	-0.0552	-0.0408	0.104	0.145***	0.0799	0.0278	-0.00348	0.00421	-0.0228	-0.0868**
	(0.0637)	(0.0508)	(0.0684)	(0.0294)	(0.0718)	(0.0506)	(0.0904)	(0.0446)	(0.0846)	(0.0407)
Constant	1.076	1.091**	-0.411	-0.512*	-0.176	0.643	0.0701	-0.00311	-0.152	0.697*
	(0.654)	(0.451)	(0.701)	(0.291)	(0.645)	(0.449)	(0.870)	(0.406)	(0.842)	(0.406)
Observations	4,347	5,231	4,138	4,138	4,097	4,912	4,212	4,212	4,243	4,243
R-squared	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Number of id	600	601	574	574	560	560	584	584	591	591
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; CI denotes computerized information; BE stands for brand equity; OC&ST indicates organization capital and staff training; the system GMM estimation in the study uses both the differenced and the lagged intangible capital as instruments.

Source: Authors' own calculation.

4.5.2 Fully analysing the heterogenous impacts: a multilevel regression approach

To take better advantage of this large dataset, multilevel regressions are conducted to assign economy and sector-specific coefficients to all individual sectors. Table 5 illustrates the baseline results from multilevel regressions. The coefficients of the intangible-tangible ratio remain close to those in Table 3 and 4 except for 'All Intangible' the scale of which is significantly larger. As for income level, all coefficients become insignificant, which indicates that the heterogeneity of its impacts in reducing sectoral energy intensity might be high. The diseconomy of scale, as revealed by the positive coefficients of aggregate GDP, remains similar to the results in Table 3. Table 6 aims to test the linear and quadratic relationship between the impacts of intangible capital on sectoral energy intensity and income level. Under the linear framework, it is found that intangible capital in an economy of higher income is likely to have lower impacts on sectoral energy intensity. Specifically, a 10% increase in income level is associated with a 0.0009 increase in the coefficient of overall intangible-tangible ratio, which is roughly 0.5% of the baseline result. For various categories of intangible capital, the increase ranges from 0.002 to 0.003, which is approximately 1% to 3% of the baseline coefficients.

When it comes to the quadratic relationship, an inverted U-shape relationship is observed. Specifically, the impact of overall intangible capital in reducing sectoral energy intensity first increases along with rising income, and when income reaches 6,759 USD per capita the impact begins to decline; the counterparts of brand equity and organization capital and staff training both also demonstrate an inverted U-shape pattern, with turning points respectively of 5772 USD per capita and 6653 USD per capita. As for R&D and computerized information, the turning point is too large for the data range and as a result they do not have a 'real' quadratic relationship.

Another interesting question to investigate is the heterogeneous impacts across sectors. Figure 2 depicts an overall picture of this heterogeneity. The pattern of the heterogeneous impacts is consistent with the results in Table 3 and 4: the service group is likely to have a higher impact than the non-service group. Within the service group, financial intermediation (J), real estate activities (70), education (M), and health and social work (N) are the largest beneficiaries from intangible capital in terms of energy intensity. The transport sectors (60, 61, 62 and 63) are the smallest beneficiaries from intangible capital within the service group. When it comes to the non-service group, the coefficients of machine nec[11] (29), electrical and optical equipment (30t33), transport equipment (34t35) and manufacturing nec, recycling (36t37) have the largest scale; the counterparts of coke, refined petroleum, and nuclear fuel (23), rubber and plastics (25), other non-metallic mineral products (26), basic metals fabricated metal products (27t28), and electricity, gas and water supply (E) have the smallest scale, which can be as low as 60% less than the benchmark coefficients. The heterogeneity of the effects of intangible capital in reducing energy intensity might be due to the heterogeneity in production structure.

[11] 'nec' means 'not else classified'.

Table 5 Baseline results derived from multilevel regressions

	Multilevel				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	All Intangible	R&D	CI	BE	OC&ST
Intangible	-0.207***	-0.0930***	-0.0940***	-0.318***	-0.155***
	(0.0278)	(0.0189)	(0.0233)	(0.0500)	(0.0251)
GDP pc	0.616	-0.227	0.878	-0.103	1.010
	(0.690)	(0.796)	(0.846)	(0.664)	(0.721)
GDP	1.470***	2.378***	1.415**	1.740***	1.136**
	(0.520)	(0.603)	(0.637)	(0.502)	(0.548)
Constant	-21.09***	-30.03***	-20.89***	-22.67***	-18.36***
	(5.408)	(6.126)	(6.233)	(5.062)	(5.594)
Observations	7,288	6,899	6,796	7,035	7,090
Number of economies	39	36	34	37	38
Number of sectors	603	576	562	586	594
Year FE	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; CI denotes computerized information; BE stands for brand equity; OC&ST indicates organization capital and staff training. The dependent variable is sectoral energy intensity.

Source: Authors' own calculation.

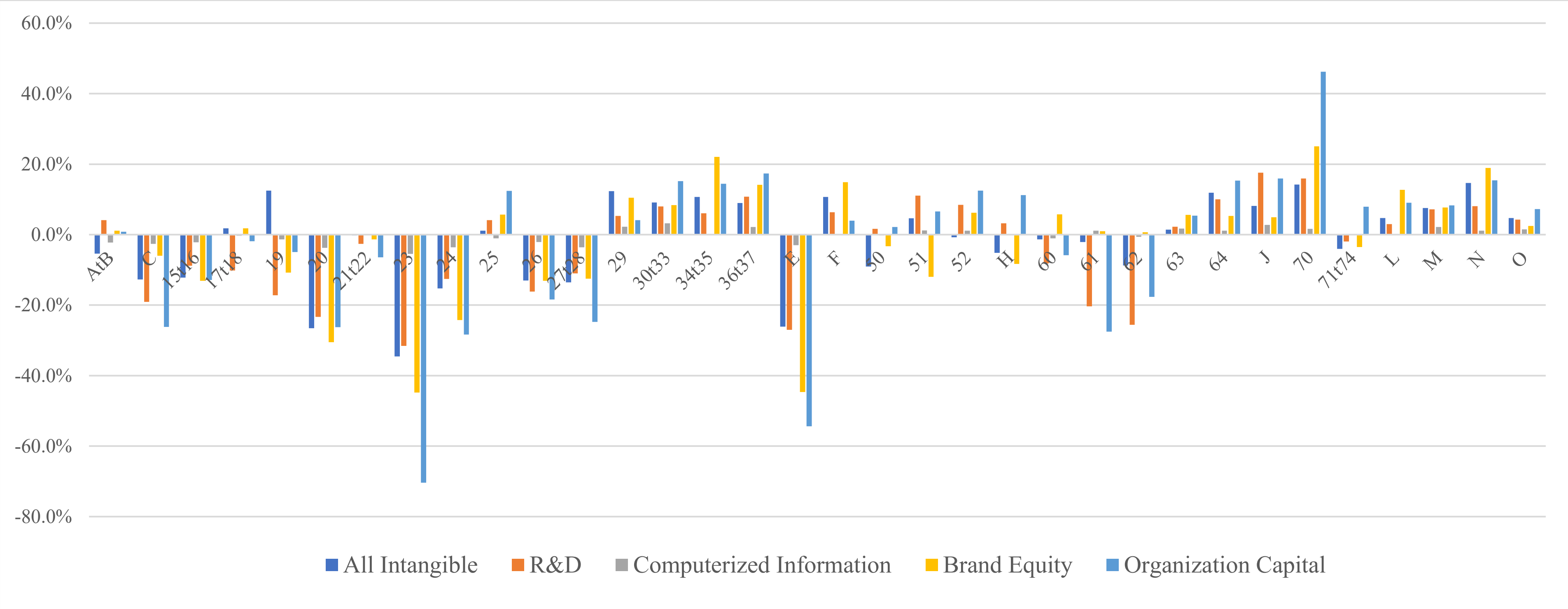
Table 6 Income level and the impacts of intangible capital on sectoral energy intensity

	Random coefficients of intangible-tangible ratio (economy level)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	All Intangible	All Intangible	R&D	R&D	CI	CI	BE	BE	OC	OC
GDP pc	0.00869***	-0.0707***	0.0250***	0.0474***	0.0292***	0.0932***	0.0279***	-0.171***	0.0197***	-0.0775***
	(0.00140)	(0.00574)	(0.000687)	(0.00292)	(0.000899)	(0.00400)	(0.00329)	(0.0139)	(0.00112)	(0.00497)
$(GDP\ pc)^2$		0.0185***		-0.00507***		-0.0140***		0.0451***		0.0221***
		(0.00129)		(0.000644)		(0.000856)		(0.00307)		(0.00110)
Constant	-0.0360***	0.0245***	-0.0533***	-0.0715***	-0.0686***	-0.125***	-0.113***	0.0487***	-0.0509***	0.0274***
	(0.00389)	(0.00572)	(0.00193)	(0.00301)	(0.00257)	(0.00429)	(0.00927)	(0.0143)	(0.00313)	(0.00495)
Observations	7,288	7,288	6,976	6,976	6,822	6,822	7,096	7,096	7,180	7,180
R-squared	0.005	0.032	0.159	0.167	0.134	0.167	0.010	0.039	0.041	0.092

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; CI denotes computerized information; BE stands for brand equity; OC&ST indicates organization capital and staff training. The dependent variable is the individual deviations from the baseline coefficients of the various types of intangible capital in Table 5. The effect of intangible capital on sectoral energy intensity is negative, which means the smaller (more negative) the coefficient the larger the effect. When there is a U-shape relationship observed in the above table, it actually indicates an inverted U-shape relationship between the income level and the effect of intangible capital in reducing sectoral energy intensity.

Source: Authors' own calculation.

Figure 2 Heterogenous impacts of intangible capital on sectoral energy intensity across various sectors (compared with baseline results)



Notes: the percentages here are the average impact difference of a sector from the baseline results.

Source: Authors' own calculation.

4.6 Conclusion and policy implications

Lowering sectoral energy intensity is a critical way to reduce energy use and then improve air quality and the environment. Although some efforts have been devoted to studying the relationship between innovation activities and energy intensity (Fisher-Vanden et al., 2004; Herrerias et al., 2016; Newell et al., 1999) as well as the correlation between intangible investment and energy intensity (Hao and van Ark, 2013), a theoretical and comprehensive analysis of the relationship between intangible capital and energy intensity is absent from the literature.

This study advances the knowledge on the relationship between intangible capital and sectoral energy intensity by taking advantage of a large dataset. Research questions examined include: Does intangible capital have a 'real' causal effect on sectoral energy intensity? How does the role of various types of intangible capital vary across economies and sectors? How does income level affect sectoral energy intensity in the context of different economies and sectors?

This study finds that a relatively robust causal relationship between intangible capital (measured as intangible-tangible capital ratio) and sectoral energy intensity exists. The increasing use of intangible capital relative to tangible capital does reduce sectoral energy intensity. However, when the income level of an economy becomes higher, intangible capital's reduction effect generally diminishes. A moderate quadratic relationship between the reduction effect of intangible capital on energy intensity and income level in some types of intangible capital is also identified. A moderate inverted

U-shape relationship exists in the overall intangible capital as well as economic competency (brand equity, organization capital and staff training), but no ‘real’ quadratic relationship is discovered for R&D and computerized information because the turning point is far beyond the data range.

Across sectors, the sectors that have the largest and smallest effects of intangible capital in reducing energy intensity within service and non-service groups are also pinpointed. Within the service group, sectors requiring a high intangible capital ratio tend to have the largest effect, and sectors relying more on physical capital are likely to have the smallest. As for the non-service group, in equipment manufacturing sector, intangible capital tends to have the largest effect, and raw materials manufacturing as well as utility sectors often have the smallest. These findings demonstrate that intangible capital can enhance the reduction effect: between sectors within each of the service and non-service sectors, the higher the ratio of intangible capital to tangible capital, the stronger the reduction effect.

Through various disaggregated analyses and multilevel regression analyses, we found a few heterogenous results: 1) brand equity and organization capital improve sectoral energy intensity more than R&D; 2) intangible capital in low and middle income economies has a larger reduction effect on sectoral energy intensity than in high income economies; 3) sectors with high intangible capital ratios in the service group and equipment manufacturing sectors in the non-service group tend to enjoy larger effects from intangible capital on sectoral energy intensity reduction; 4) income level generally decreases the effect of intangible capital in reducing sectoral energy intensity but a moderate inverted U-shape relationship between income level and the effect of intangible capital in reducing sectoral energy intensity is identified in aggregate intangible capital as well as some disaggregated intangible capital including brand equity and organization capital.

The study offers the following policy implications:

First, in addition to usual R&D, branding equity such as advertisement and staff training are found to be new instruments to reduce energy intensity. These new policy instruments that support the role of intangible capital in reducing energy intensity complement the literature.

Second, in terms of global energy intensity reduction, the role of intangible capital should be strengthened in developing economies, where the marginal reduction effect of intangible capital is higher. This would also suggest cooperation and transfer of intangible investment because developing economies often have less intangible capital than developed ones.

Lastly, within a country, development of sectors with high intangible and tangible capital ratio can reduce the overall intensity. Furthermore, the reduction effect of energy intensity would be boosted if a unit of intangible capital is allocated to the sector with higher intangible capital-capital ratio. For example, in the non-service sector, energy intensity could be reduced by reallocating intangible capital to the manufacturing industry from other industries.

Future research directions might include investigating firm-level evidence on the relationship between energy intensity and intangible capital when relevant data is fully available.

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4.7 Appendix A

This appendix demonstrates the derivation of structural decomposition analysis (SDA) equation in section 2.

From the well-known Leontief input-output model, the following equilibrium equation is obtained:

$$X = (I - A)^{-1}Y \tag{A.1}$$

X is the vector of sectoral gross output; A is the matrix of technical coefficients and y is the vector of final demand. $(I - A)^{-1}$ is the famous Leontief inverse.

In the following, the diagonalization and transposition of a matrix are respectively denoted by ^ and $'$. Assume e to be a vector of direct consumption of energy. Then the direct energy intensity ε is defined as follows:

$$\varepsilon = e'\widehat{X}^{-1} \tag{A.2}$$

Then the following is obtained:

$$e = \hat{\varepsilon}X \tag{A.3}$$

Substitute the value of X, taking into account (A.1) and (A.3), then a small transformation leads to:

$$E = \hat{\varepsilon}(I - A)^{-1}\hat{Y}$$

E shows the total consumption, direct and indirect, of the different sectors. The sum of all the elements in E is the total energy consumption.

4.8 Appendix B

WIOD sectors, definition by NACE and the classification of sectors

NACE	WIOD sectors	Classification
AtB	Agriculture, hunting, forestry and fishing	Non-service
C	Mining and quarrying	Non-service
15t16	Food, beverages and tobacco	Non-service
17t18	Textiles and textile products	Non-service
19	Leather, leather products and footwear	Non-service
20	Wood and products of wood and cork	Non-service
21t22	Pulp, paper, paper products, printing and publishing	Non-service
23	Coke, refined petroleum and nuclear fuel	Non-service
24	Chemicals and chemical products	Non-service
25	Rubber and plastics	Non-service
26	Other non-metallic mineral products	Non-service
27t28	Basic metals and fabricated metal products	Non-service
29	Machinery nec	Non-service
30t33	Electrical and optical equipment	Non-service
34t35	Transport equipment	Non-service
36t37	Manufacturing nec, recycling	Non-service
E	Electricity, gas and water supply	Non-service
F	Construction	Non-service
50	Sale, maintenance and repair of motor vehicles	Service
51	Wholesale trade and commission trade	Service
52	Retail trade, except motor vehicles and motorcycles	Service
H	Hotels and restaurants	Service
60	Inland transport	Service
61	Water transport	Service
62	Air transport	Service
63	Supporting and auxiliary transport activities	Service
64	Post and telecommunications	Service
J	Financial intermediation	Service
70	Real estate activities	Service
71t74	Renting of machinery and equipment and other business activities	Service
L	Public administration and defence, social security	Service
M	Education	Service
N	Health and social work	Service
O	Other community, social and personal services	Service

5. Intangible capital, productivity spillover and economic growth: Cross-country evidence

Intangible capital has been well documented as an important source of economic growth. However, studies on its heterogeneous role remain rare. How do its output elasticity and productivity spillover of economic growth vary across sectors and economies at different development stages? This study advances the understanding on this issue by taking advantage of a rich dataset of 40 economies derived from the World Input-Output Database (WIOD), spanning over 13 years (1995 – 2007). It is found that intangible capital significantly contributes to economic growth as a production factor as well as through its productivity spillover effect. Both its output elasticity and productivity spillover effect demonstrate an inverted U-shape relationship with income level and significantly vary across sectors. The productivity spillover effect is generally larger in service sectors than non-service sectors. The findings provide some useful implications for policy makers as well as studies on income inequality.

5.1 Introduction

Intangible capital is the immaterial resources that enter the production process and is important for both the creation and the improvement of products as well as production process. Intangible capital has been widely accepted as a key production factor in the literature, especially for developed economies. Therefore, it is not surprising that much effort is devoted to studying its role as a source of growth and productivity spillover both at national level and sectoral level (Awano et al., 2010; Borgo et al., 2013; Chun and Nadiri, 2016; Corrado et al., 2017, 2013, 2009; Corrado and Hulten, 2010; Fukao et al., 2009; Haskel and Wallis, 2013; Marrano et al., 2009; Miyagawa and Hisa, 2013; Niebel et al., 2017; van Ark et al., 2009). While the growth and productivity spillover effect of intangible capital is well documented, its heterogeneous output elasticity and productivity spillover effects across economies at different development stages and various sectors have received relatively little attention. The income share or output elasticity of intangible capital might be associated with changes in income level, and thus play an important role in the dynamic of income inequality. Moreover, the spillover effect of intangible capital might also significantly differ across economies and sectors, and understanding its pattern is of importance for policy makers.

This study aims to advance the knowledge on the heterogeneous role of intangible capital in economic development by taking advantage of a rich worldwide dataset derived from the World Input-Output Database (WIOD) developed within the 7th Framework Programme of the European Commission, and provide a more comprehensive analysis on how the role of intangible capital in economic growth varies across economies and sectors. Specifically, this study constructs a sectoral level dataset for 34 sectors across 39 economies[1] spanning from 1995 to 2007 based on the World Input-Output Database (WIOD) and makes use of the economy and sector-specific coefficients generated by the multilevel analysis to reveal how production structure and productivity spillover effects change between different economies and sectors.

Another motivation of this study is to examine the role of income level in determining

[1] Excluding China is due to the lack of data on the number of employees.

the output elasticity and productivity spillover of intangible capital. Physical capital's income share has been well recognized to have an inverted U-shape relationship with income level (Kuznets, 1955; Milanovic, 1994), which is also supposed to be one of the key factors that drive the dynamic of income inequality. Specifically, at the early stage of development, physical capital is scarce and income is often distributed in favour of the owners of physical capital; as economic development passes a certain point, physical capital becomes sufficiently abundant to allow the income to be distributed more favourably towards the labour. Although the importance of intangible capital has been widely regarded, the relationship between its income share and income level has not received much attention. The study of its income share dynamic with respect to income level might provide key information for future research on income inequality. It is possible that the income share of intangible capital also demonstrates an inverted U-shape relationship with income level but has a significantly different turning point. If such an interesting fact exists, then the stories on the dynamic of income inequality might need a new component. In addition to the income share, the productivity spillover effect has also been proved to be associated with income level. For instance, the productivity spillover of foreign direct investment (FDI) has an inverted U-shape with income level: it first increases as income increases due to increasing absorptive capacity (Findlay, 1978; Gerschenkron, 1962; Wang and Blomström, 1992), and then decreases as income increases because of decreasing technology gap (Kinoshita, 2001.; Lapan and Bardhan, 1973; Perez, 1997; Wang and Blomström, 1992). Although the productivity spillover of FDI has been well studied, relevant issues on intangible capital remain unclear. Understanding these relevant issues might provide useful insights for policy makers, especially when some intangible investment is guided by public policies.

When it comes to the methodology and data, this study differs from previous literature on intangible capital. When estimating the production function, most of the literature adopts the income share approach, which does not allow error term and therefore relies heavily on the measurement accuracy of intangible capital[2]. Some literature uses regressions with constant coefficients, which allows error term but causes the loss of sector and economy specific information. The estimation of the production function in this study is based on multilevel analysis instead of income share approach or regressions with constant coefficients and is a balance between tolerating the measurement inaccuracy of intangible investment and acquiring economy and sector-specific information. This approach constitutes an improvement to previous approaches in the literature. Moreover, this study includes data with a more detailed sector classification as well as data from developing economies and thus allows further inquiry into the heterogeneous roles of intangible capital in sectoral production structure and productivity spillover, providing a new angle from which the roles of intangible capital are examined. From the perspective of the literature stream on intangible capital, this study complements the literature confirming intangible investment as a source of growth (Corrado et al 2009; Fukao et al. 2009; van Ark et al. 2009; Marrano et al 2009; Awano et al. 2010; Corrado and Hulten 2010; Borgo et al. 2013; Corrado et al. 2013; Haskel and Wallis 2013; Miyagawa and Hisa 2013; Chun and Nadiri 2016; Niebel et al. 2017) and the literature confirming the existing of productivity spillover of intangible

[2] Corrado et al. (2009) also admit the inaccuracy of the intangible capital measurement they propose, as revealed by the last sentence of their paper, ‘it is better to be imprecisely right than precisely wrong’.

capital (Corrado et al. 2017).

This paper is organized as follows: section two discusses the definition and measurement of intangible capital; section three depicts the empirical strategies adopted as well as relevant data sources used; section four reports the empirical results; section five draws the conclusion.

5.2 Intangible capital: definition and measurement

To construct the series of intangible capital, the first step is to define and measure the flow of intangible investment. Two streams of definitions of intangible capital co-exist in the literature. One is based on the accounting concept of intangible assets and is acquired from firms' balance sheets; this definition is often used in firm-level analysis (Marrocau et al. 2012). The other is derived from the aggregate estimates of firms' intangible expenditure such as R&D, advertising and innovation (Corrado et al. 2009). Given that this study focuses on sectoral level, it is more appropriate to adopt the expenditure based approach. Three categories of intangible investment are calculated from the intermediates of the supply and use tables within the WIOD (for information of the WIOD, please see Timmer et al. (2015)) based on the capitalization criteria of Corrado et al. (2009), as summarized in Table 1. The accumulation of intangible capital follows the standard perpetual inventory method:

$$\mathrm{IC}_{s,t} = \mathrm{IC}_{s,t-1}(1-\delta_s) + IN_{s,t}$$

where IC refers to intangible capital; the subscripts *s* and *t* respectively denote the intangible capital *s* and the time; δ refers to the depreciation rate; IN is the intangible investment. To implement the law of motion of intangible capital, an initial intangible capital stock must be chosen, which is according to

$$\mathrm{IC}_{s,0} = \frac{IN_{s,0}}{g_s + \delta_s}$$

where g_s is chosen to match the average real growth rate of the intangible investment s in a sector. Compared with the national level measurement of Corrado et al. (2009) and the literature following it, this measurement might be of lower accuracy. The source of inaccuracy might be caused by the deviation of the measured outsourcing ratio from the actual outsourcing ratio, 'other business activities' intermediates including expenditure that is not intangible investment, the distribution of computerized information investment across sectors inconsistent with that of 'computer and related services' intermediate etc. However, since the econometrics approach used in this study has some tolerance of measurement error, the constructed dataset should satisfy the analysis requirement[3].

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[3] If the measurement error is randomly distributed, it will not cause bias in the estimation results; if the measurement error is sector-specific, then it will be eliminated by the sector specific intercept.

Table 1 Measurement and depreciation rate of intangible investment

Intangible investment	Method	Depreciation rate[4]
Computerized information	Distribute the aggregate gross fixed investment in computerized information according to the use of 'computer and related services' intermediate	0.33
Innovative property	Use 'research and development services' intermediate adjusted by the outsourcing ratio	0.2
Economic competency		
Brand equity (advertising)	Use 60%[5] of 'other business activities'[6] adjusted by the outsourcing ratio	0.6
Organization capital and staff training[7]	Use 'education services' intermediate adjusted by the outsourcing ratio	0.4

Notes: Outsourcing ratio is defined as the ratio of the value added to total intermediates. The reason why the intermediates statistics should be adjusted by the outsourcing ratio is that in the supply and use tables only outsourced intangible expenditure is counted and directly using the intermediate statistics neglects the internally produced intangible expenditure.

Source: Authors' own construction.

5.3 Empirical strategies and data sources

5.3.1 Empirical strategies

Intangible capital has been widely confirmed as a critical production factor, and it is therefore necessary to incorporate intangible capital into the production function to avoid estimation bias. Therefore, the production function in the Cobbs-Douglas[8] form should be

$$\mathrm{Y}_{i,j} = \mathrm{A}_{i,j}\mathrm{IC}_{i,j}{}^{\alpha_{i,j}}\mathrm{K}_{i,j}{}^{\beta_{i,j}}\mathrm{L}_{i,j}{}^{\gamma_{i,j}} \tag{1}$$

where Y is the value added of a sector; A represents the total factor productivity (TFP); IC stands for intangible capital; K symbolizes physical capital; L indicates labour; subscripts i, j respectively denote sector i in economy j.

By taking the logarithm in both sides, the production function is then linearized as

[4] The depreciation rate follows Corrado et al. (2009).

[5] Corrado et al. (2009) estimate 60% of the advertising expenditure should be capitalized.

[6] 'Other business activities' includes advertising expenditure and market research.

[7] Organization capital and staff training refers to the firm-specific human and structural resources (Corrado et al. 2009), which can be indicated by the education expenditure of firms.

[8] No restriction on return to scale is imposed in this case given the sectoral heterogeneity.

$$\log(\mathrm{Y}_{i,j}) = \log(\mathrm{A}_{i,j}) + \alpha_{i,j}\log(\mathrm{IC}_{i,j}) + \beta_{i,j}\log(\mathrm{K}_{i,j}) + \gamma_{i,j}\log(\mathrm{L}_{i,j}) \qquad (2)$$

To generate economy and sector-specific coefficients for each input, multilevel regressions are then applied. Specifically, a two-level hierarchy structure is identified: economy level and sector level. The output elasticity of each input factor thus comprises three elements: the baseline coefficient, the economy specific deviation as well as the sector-specific deviation. To complement the literature on the income inequality (Kuznets 1955; Milanovic 1994), it is helpful to study the relationship not only between income level and intangible capital income share[9] but also between income level and tangible capital income share[10]. The first step is to construct two new variables to capture respectively intangible capital income share relative to that of labour as well as between that of tangible capital and relative to that of labour, which are as follows:

$$\mathrm{D}_{IC} = \alpha_{i,j} - \gamma_{i,j} \qquad (3)$$

and

$$\mathrm{D}_{K} = \beta_{i,j} - \gamma_{i,j} \qquad (4)$$

where D_{IC} is the intangible capital income share relative to that of labour; D_{K} is the tangible capital income share relative to that of labour. Based on the measurements from (3) and (4), the linear and quadratic relationship between income level and the relevant capital income share is then tested:

$$\mathrm{D} = \mathrm{a}_1\ln(\text{GDP per capita}) + \mathrm{a}_2 \qquad (5)$$

and

[9] Theoretically, the output elasticity of an input factor equals its income share.
[10] Physical capital's income share has been well recognized to have an inverted U-shape relationship with income level (Kuznets, 1955; Milanovic, 1994), which is also supposed to be one of the key factors that drive the dynamic of income inequality. Examining the relationship between capital income share and per capita income will help better understand the income inequality dynamic in different development stages, as mentioned in the introduction.

$$\mathrm{D} = \mathrm{b}_1 \ln(\text{GDP per capita})^2 + \mathrm{b}_2 \ln(\text{GDP per capita}) + \mathrm{b}_3 \quad (6)$$

When output elasticity of each sector is acquired, the next step is to calculate the total factor productivity (TFP). Based on equation (2), the TFP is derived according to

$$\log(\mathrm{A}_{i,j}) = \log(\mathrm{Y}_{i,j}) - \alpha_{i,j} \log(\mathrm{IC}_{i,j}) + \beta_{i,j} \log(\mathrm{K}_{i,j}) + \gamma_{i,j} \log(\mathrm{L}_{i,j}) \quad (7)$$

The productivity spillover effect is often defined as the use of production factors in one firm contributing to the productivity of another firm. To examine the spillover effect of intangible capital on productivity within a sector, the below double differenced empirical model is assumed to eliminate the possible serial correlation, following Corrado et al. (2017)[11]

$$\Delta(\Delta \log \mathrm{A}_{i,j}) = di_{i,j} \Delta(\Delta \log \mathrm{IC}_{i,j}) + dk_{i,j} \Delta(\Delta \log \mathrm{K}_{i,j}) + dl_{i,j} \Delta(\Delta \log \mathrm{L}_{i,j}) + \mathrm{constant}_{i,j}$$

(8)

If there is a productivity spillover effect from intangible capital, then $di_{i,j}$ should be positive and significant. Given that the regression to be conducted is multilevel analysis, economy and sector-specific coefficients will then be derived, which forms the basis for research on the heterogeneity in the magnitude of the spillover effect across various economies and sectors. The analysis steps are similar to those on the heterogeneity in the output elasticity of intangible capital. Econometric analysis is conducted at economy level while graphing approach is applied at sectoral level.

Finally, a partially replicated experiment based on Corrado et al. (2017) but with some

[11] We assume the derivation of productivity measure in equation (7) is technically correct. Based on the assumption, regressing second-differenced productivity on second-differenced production factors examines the impact of increased use of production factors on productivity, assuming sectors/economies have their individual productivity/production factor growth acceleration.

new components is conducted to discuss the heterogenous spillover effects of the disaggregated intangible capital.

5.3.2 Data sources and summary statistics

The data used in this study mainly comes from the WIOD. The WIOD database has two main advantages compared with previously available data sources. First, throughout the data collection efforts, harmonization procedures were applied to ensure international comparability of the data. This ensures data quality and minimizes the risk of measurement errors. Second, the WIOD includes sectoral price deflators, the use of which allows one to retain important information and the heterogeneity of the sectors with respect to price dynamics. This represents an improvement over the use of aggregate national price deflators. A complete list of the 34 sectors included in the database is shown in Appendix A. The construction of intangible capital data, as mentioned in Section 2, is based on the intermediates statistics from the supply and uses tables within the WIOD. Value added, number of labour and tangible capital at sector level are derived from the Social Economic Accounts within the WIOD. All data derived from the WIOD is deflated to 1995 constant USD using sector-specific deflators and the exchange rate of 1995 USD. In terms of income level, the GDP per capita is obtained from the Penn World Table 8.1[12] and also deflated to 1995 constant USD. The relevant variables and their descriptive statistics are summarized in Table 2 below. The range and variation of the variables can be clearly seen, showing that the sample contains heterogenous observations from various economies and sectors. The mean of

[12] For a detailed introduction to the Penn World Table 8.1, please see Feenstra et al. (2015).

sector value added is 3.2 billion constant 1995 USD; the average number of employees is 89 thousand; the average amount of tangible capital and intangible capital are respectively 7.5 billion and 512 million constant 1995 USD; the mean of GDP per capita is 14 thousand constant 1995 USD.

Table 2 Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
ln(Value added)	overall	8.14656	1.889557	2.139389	17.64552	N = 6385
	between		1.796914	3.072364	14.78587	n = 545
	within		0.62322	2.7139	11.60706	T-bar = 11.75
ln(Labour)	overall	4.562983	1.337652	0	6.904751	N = 6403
	between		1.365018	0	6.900729	n = 545
	within		0.151984	3.471657	6.061924	T-bar = 11.75
ln(Tangible capital)	overall	8.934774	1.762157	3.803996	14.43591	N = 6403
	between		1.761926	4.24738	14.42826	n = 545
	within		0.246267	7.371815	10.53017	T-bar = 11.75
ln(Intangible capital)	overall	6.311915	2.538113	-5.58173	21.77141	N = 6403
	between		2.357375	-2.12384	20.9065	n = 545
	within		0.960658	-4.50928	15.02492	T-bar = 11.75
ln(GDP per capita)	overall	2.579061	1.048186	-0.95819	4.359776	N = 6403
	between		1.063807	-0.91461	4.16471	n = 545
	within		0.141569	2.120187	3.126091	T-bar = 11.75

Source: Authors' own calculation based on data from the WIOD and the Penn World Tables 8.1.

5.4 Empirical results

Table 3 demonstrates the baseline results for the multilevel analysis. Consistent with the expectation, all three production factors are positive and statistically significant. Tangible capital on average has the largest output elasticity and labour follows. Unsurprisingly, intangible capital has the smallest but its magnitude (approximately two thirds of that of tangible capital) indicates that it is indeed a key production factor in today's modern economy. Table 4 displays the relationship between income level and income share of intangible capital and tangible capital. Under the linear framework, it is found that the income share of both types of capital relative to labour is decreasing along with rising income level, which is consistent with the literature on income inequality (Kuznets 1955; Milanovic 1994). However, the magnitude of the relationship across two types of intangible capital is significantly different. Specifically, a 10% increase in income level is associated with a 0.011 decrease in the gap between tangible capital income share and labour income share but only associated with a 0.0042 decrease in the gap between intangible capital income share and labour income share, which might indicate that tangible capital plays a more important role in alleviating income inequality in the long run. Under the quadratic framework, an inverted U-shape relationship is identified in both types of capital, which complements the literature that identifies a Kuznets curve for the relationship between income inequality and income level (Kuznets 1955; Milanovic 1994). Both Kuznets (1995) and Milanovic (1994) argue that there is an inverted U-shape between income level and physical capital income, which may be one of the key drivers of the dynamics of income inequality. While the results in Table 4 confirm this relationship based on evidence from 39 economies, it is worth noting that both the magnitude and the turning point of the relationship differ between the two types of capital. The inverted U-shape of intangible capital is 'slimmer' than that of tangible capital, as indicated by the larger scale of the coefficient of the square term. Moreover, the turning point of tangible capital is much lower than that of intangible capital: 1,120 1995 USD for tangible capital and 7,000 1995 USD for intangible capital, which complements the results of Milanovic (1994). Milanovic (1994) finds that the turning point in the relationship between Gini Index and income level is $2,100 per capita (at 1988 international price), which is between the turning point of intangible capital and tangible capital in this study. The two turning points revealed in this study might support a hypothesis that the increasing income inequality in the low and middle income stage is first driven by the increasing income share of both tangible capital and intangible capital and then mainly driven by the increasing income share of intangible capital.

Table 3 Production function estimation (Multilevel analysis, baseline result)

VARIABLES	Coefficient	Standard Error	Significance Level
ln(Labour)	0.312	0.0571	***
ln(Tangible Capital)	0.365	0.0745	***
ln(Intangible Capital)	0.223	0.0315	***
Constant	2.652	0.648	***
Observations	6,385		
Number of economies	39		
Number of sectors	34		
Year FE	YES		

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own calculation.

Table 4 Income level and income share of intangible and tangible capital

	(1)	(2)	(3)	(4)
VARIABLES	Intangible Capital	Intangible Capital	Tangible Capital	Tangible Capital
ln(GDP per capita)	-0.0419***	0.167***	-0.105***	0.00511
	(0.00262)	(0.0144)	(0.00274)	(0.0153)
ln(GDP per capita)^2		-0.0429***		-0.0226***
		(0.00290)		(0.00308)
Constant	-0.0911***	-0.305***	0.162***	0.0491***
	(0.00756)	(0.0163)	(0.00791)	(0.0173)
Observations	5,302	5,302	5,302	5,302
R-squared	0.046	0.084	0.217	0.225

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own calculation.

When it comes to the productivity spillover effect of intangible capital, Table 5 gives an overall result that is consistent with Corrado et al. (2017). Intangible capital demonstrates a positive and significant coefficient while both labour and tangible capital have a negative but insignificant coefficient, which indicates that the spillover effect does exist in intangible capital but is not significant for both labour and tangible capital. The coefficient of the spillover effect (0.04), however, is smaller than that of Corrado et al. (2017) (approximately 0.20), which might be due to the fact that the multilevel analysis in this study has controlled for sector fixed effects. Controlling for sector fixed effects allows individual sectors to have their own trend in the change in productivity growth rate, which might be an improvement compared with Corrado et al. (2017). For instance, some traditional sectors such as basic metals and fabricated metal products might demonstrate a decrease in the rate of productivity growth in contrast to some rising sectors, which might be correlated with the change in the rate of intangible capital growth. In order to quantitatively measure the magnitude of the spillover effect, it is necessary to first calculate the average growth rate of intangible capital and in this case it is 5.5%. Then the scale of the spillover effect of intangible capital is approximately 0.22 (5.5×0.04=0.22) percentage point, which is slightly above one fourth of that in Corrado et al. (2017). Nevertheless, the productivity spillover effect remains both economically and statistically significant, even after imposing an additional restriction (sector fixed effect).

Table 5 Spillover effect of intangible capital (baseline results)

VARIABLES	
$\Delta(\Delta \ln \text{Labour})$	-0.152
	(0.179)
$\Delta(\Delta \ln \text{Tangible Capital})$	-0.408
	(0.297)
$\Delta(\Delta \ln \text{Intangible Capital})$	0.0400***

	(0.0129)
Constant	0.0491
	(0.0336)
Observations	3,778
Number of sector	33
Number of economy	39
Year FE	YES

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculation.

To further explore the heterogeneity in the spillover effect across various economies, both linear and quadratic frameworks are applied and the results are illustrated in Table 6. It is found that income level is significantly and negatively correlated with the magnitude of the spillover effect and an insignificant quadratic relationship is also identified. Specifically, a 10% increase in income level is associated with a 0.001 decline in the spillover effect, which is approximate 2.5% of the baseline coefficient. In respect of the quadratic relationship, the turning point is 2,300 1995 USD. The result provides new information for the literature on productivity spillover effects. The magnitude of the productivity spillover effect is often found to follow a quadratic relationship. For example, the productivity spillover effect of FDI first increases with increasing income due to absorptive capacity (Gerschenkron 1962; Findlay 1978; Wang and Blomström 1992), and then decreases as income increases because of decreasing technology gap (Lapan and Bardhan 1973; Wang and Blomström 1992; Perez 1997; Kinoshita 2001). In the case of intangible capital, the story might be similar. Intangible capital, in the context of low income economies, is often used by the leading firms. The spillover effects of various types of intangible capital including computerized information, innovative property, brand equity, organization capital and staff training might also be subject to absorptive capacity. When the economy passes a certain threshold and the use of intangible capital becomes more common, the spillover effect then declines. Although this hypothetical mechanism cannot be proved, the inverted U-shape relationship found in this study provides some hints on further studies on the mechanism.

Table 6 Income level and the spillover effects

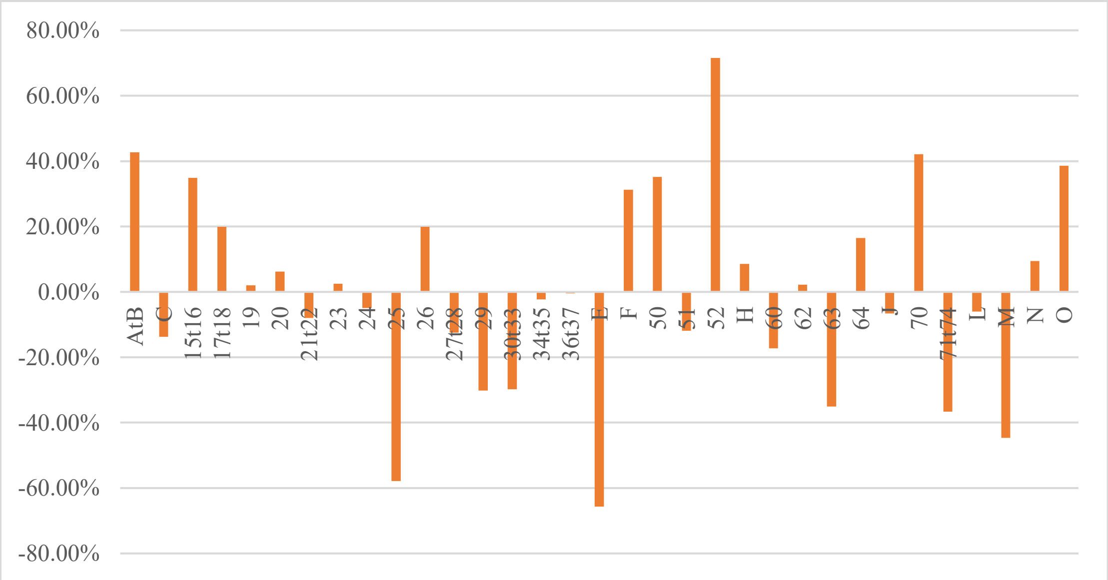
VARIABLES	(1)	(2)
ln(GDP per capita)	-0.00927***	0.00538
	(0.00122)	(0.00683)
$\ln(\text{GDP per capita})^2$		-0.00300**
		(0.00138)
Constant	0.0245***	0.00951
	(0.00352)	(0.00772)
Observations	5,291	5,291
R-squared	0.011	0.012

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' own calculation.

Another interesting question to explore is the heterogeneity of productivity spillover across sectors. Figure 1 provides the relevant information. From the figure, it is clear that the service group generally has a larger intangible capital spillover effect than the non-service group. Retail trade enjoys the largest scale while rubber and plastics has the smallest. Other sectors that significantly deviate from the baseline result comprise agriculture, hunting, forestry and fishing (AtB) (+), food, beverages and tobacco (15t16) (+), textiles and textile products (17t18) (+), other non-metallic mineral products (26) (+), construction (F) (+), sale, maintenance and repair of motor vehicles (50) (+), post and telecommunications (64) (+), real estate activities (70) (+), other community, social and personal services (O) (+), mining and quarrying (C) (-), pulp, paper, paper products, printing and publishing (21t22) (-), basic metals and fabricated metal products (27t28)

(-), machinery nec (29) (-), electrical and optical equipment (30t33) (-), electricity, gas and water supply (E) (-), wholesale trade and commission trade (51) (-), Inland transport (60) (-), supporting and auxiliary transport activities (63) (-), renting of machinery and equipment and other business activities (71t74) (-), and education (M) (-). There are also many sectors having a similar magnitude to the baseline result, including leather, leather products and footwear (19), coke, refined petroleum and nuclear fuel (23), chemicals and chemical products (24), transport equipment (34t35), manufacturing nec, recycling (36t37), air transport (62), financial intermediation (J), and public administration and defence, social security (L). The observations on the heterogeneity of spillover effect across various sectors might support a hypothesis that sectors relying more on intangible capital have a larger productivity spillover effect from intangible capital, which is consistent with Keller and Yeaple (2009) who find that firms in high-tech sectors enjoy larger productivity spillover effect based on evidence from US firms. However, to confirm this hypothesis, further study is needed.

Figure 1 Productivity spillover of intangible capital across sectors



Source: Authors' own construction.

To explore the heterogeneous productivity spillover effects of different components of intangible capital, it is beneficial to partially replicate the experiment of Corrado et al. (2017) but with some extra interaction terms to compare the heterogeneity coefficients across sector groups and income stages. Mutilevel analysis is no longer used because of the significantly increased number of variables, which might lead to the number of coefficients to be estimated surging. Specifically, intangible capital will be disaggregated into computerized information, innovative property and economic competency, and then lags of production factors will be added into the regressions. Moreover, interaction terms between service group as well as income level and various types of intangible capital are incorporated into the regressions. Relevant results are demonstrated in Table 7. Due to data availability issues, tangible capital is not classified into ICT and non-ICT, and labour hour is also not included into the regressions. Nevertheless, the experiment in this study focuses more on the heterogeneity of the spillover effect and may provide some useful information. The results in Table 7 are generally consistent with those of Corrado et al. (2017): the spillover effect of innovative property (R&D) is only found in its first lag and that of economic competency is found in the current period. However, no consistent evidence supports the spillover effect of computerized information, given that the sign of its coefficient changes after interaction terms are incorporated. When it comes to the heterogenous spillover effect, it is found that higher income is correlated with a lower spillover effect and the service group has a larger spillover effect than non-service group, both for R&D and economic competency, which is consistent with the findings in Table 6 and Figure

1. Specifically, the spillover effect of R&D in the service group is 1.5 percentage point higher than that of the non-service group, and that of economic competency is 16 percentage point larger than the non-service group. When income increases by 10%, the productivity spillover effect of R&D is predicted to decline by 0.2 percentage point and that of economic competency will decrease by 0.7 percentage point, which is consistent with the results in Table 6. The findings on the role of different categories of intangible capital reveal that in the modern economy not only R&D but also non-R&D has significant impacts on productivity, and their interactions with income level and sector-specific characteristics are consistent with the findings based on aggregated intangible capital data.

Table 7 Spillover effects of various types of intangible capital

VARIABLES	(1)	(2)
$\text{L1.}\Delta(\Delta\ln\text{R\&D})$	0.00639	0.0503**
	(0.0109)	(0.0220)
$\Delta(\Delta\ln\text{EC})$	0.285***	0.407***
	(0.0151)	(0.0349)
$\Delta(\Delta\ln\text{EC})\times\ln(\text{GDP per capita})$		-0.0685***
		(0.0114)
$\text{L1.}\Delta(\Delta\ln\text{R\&D})\times\ln(\text{GDP per capita})$		-0.0200***
		(0.00717)
$\Delta(\Delta\ln\text{EC})\times\text{Service}$		0.0147
		(0.0135)
$\text{L1.}\Delta(\Delta\ln\text{R\&D})\times\text{Service}$		0.164***
		(0.0204)
$\Delta(\Delta\ln\text{CI})$	-0.0157***	0.0397***
	(0.00591)	(0.0143)
$\text{L1.}\Delta(\Delta\ln\text{CI})$	-0.00503	-0.00473
	(0.00598)	(0.00587)
$\Delta(\Delta\ln\text{CI})\times\ln(\text{GDP per capita})$		-0.0197**
		(0.00764)
$\Delta(\Delta\ln\text{CI})\times\text{Service}$		-0.0510***
		(0.00853)
$\Delta(\Delta\ln\text{Labour})$	-0.205	-0.183
	(0.129)	(0.126)
$\Delta(\Delta\ln\text{Tangible})$	-0.433*	-0.458*
	(0.263)	(0.257)
$\text{L1.}\Delta(\Delta\ln\text{Labour})$	-0.0735	-0.0216
	(0.129)	(0.127)
$\text{L1.}\Delta(\Delta\ln\text{Tangible})$	0.294	0.226
	(0.249)	(0.243)
Constant	-0.0451	-0.0532
	(0.0354)	(0.0346)
Observations	2,967	2,967
R-squared	0.181	0.223
Year FE	YES	YES

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' own calculation.

5.5 Discussions and Conclusion

In this study, the heterogeneous role of intangible capital in production and productivity spillover is investigated based on sectoral level data for 39 economies constructed from the WIOD, which contribute to the literature confirming intangible capital as a source of growth, the literature confirming the productivity spillover effect of intangible capital, and the literature related to income inequality as well as to the pattern of productivity spillover effects. In order to construct a sufficiently large dataset for the heterogeneity analysis, the method of this study might have sacrificed some accuracy compared with the method used in constructing national level data by Corrado et al. (2009) and the literature following it. The source of inaccuracy might be caused by the deviation of the measured outsourcing ratio from the actual outsourcing ratio, 'other business activities' intermediates including expenditure that is not intangible investment, the distribution of computerized information investment across sectors inconsistent with that of 'computer and related services' intermediate etc. Nevertheless, the econometric method deployed in this study has some tolerance of measurement error, which is likely to make the constructed dataset satisfy the analysis requirement[11]. Multilevel analysis that is a balance between tolerating the measurement inaccuracy of intangible investment and acquiring economy and sector-specific information is applied to retrieve the economy and sector-specific coefficients for the production function and spillover effect of intangible capital. A partially replicated experiment of Corrado et al. (2017) is then conducted to study the heterogenous spillover effects of the disaggregated intangible

[11] If the measurement error is randomly distributed, it will not cause bias in the estimation results; if the measurement error is sector-specific, then it will be eliminated by the sector specific intercept.

capital.

It is found that intangible capital significantly contributes to sectoral value added with an average output elasticity as large as two thirds of that of tangible capital. An inverted U-shape relationship between capital income share of both types of capital (relative to labour income share) and income level has also been identified based on the heterogeneous output elasticity derived from the multilevel analysis, which indicates both tangible and intangible capital might play an important role in the income inequality dynamic. Moreover, the turning point of intangible capital income share is larger than that of tangible capital income share, which might support a hypothesis that the increasing income inequality in the low and middle income stage is first driven by the increasing income share of both tangible capital and intangible capital, and then driven by the increasing income share of intangible capital.

When it comes to the productivity spillover of intangible capital, the results are consistent with those of Corrado et al. (2017) but include further inquiry into the heterogeneity of the effect. Among labour, tangible capital and intangible capital, only intangible capital is found to have significant productivity spillover effects, aligned with the findings of Corrado et al. (2017). Income level is generally negatively correlated with the productivity spillover effect, and there is moderate evidence supporting an inverted U-shape relationship between the magnitude of the intangible capital spillover effect and income level, which complements the literature on the inverted U-shape relationship between income level and the productivity spillover effect (Gerschenkron

1962; Findlay 1978; Wang and Blomström 1992; Lapan and Bardhan 1973; Perez 1997; Kinoshita 2001). The sector-average spillover effect has also been qualitatively studied. Based on the graphic approach, the spillover effect shows a pattern of larger spillover effects in sectors relying more on intangible capital, which is consistent with the findings of Keller and Yeaple (2009) that firms in high-tech sectors enjoy larger productivity spillover effect based on evidence from US firms.

Finally, a partially replicated experiment of Corrado et al. (2017) reveals the heterogenous spillover effects of different types of intangible capital. It is found that the first lag of R&D component and the current period of economic competency component demonstrates significant spillover effects on productivity, consistent with Corrado et al. (2017). However, no robust evidence supports the spillover effect of computerized information. The spillover effects of both R&D and economic competency show a consistent pattern: the effect is larger in the service group than the non-service group and decline as income increases.

The findings of this study partially answer the questions on the heterogeneous output elasticity and productivity spillover of intangible capital across sectors and economies, which might provide useful information for explaining the relationship between income inequality and economic growth. Policy makers might also find the information helpful by better understanding the changing roles of intangible capital in determining productivity spillover and then economic growth. Future research directions might include investigating firm-level evidence on the relationship between intangible capital and productivity spillover when relevant data is fully available.

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5.6 Appendix A

WIOD sectors, definition by NACE and sector classification

NACE	WIOD sectors	Classification
AtB	Agriculture, hunting, forestry and fishing	Non-service
C	Mining and quarrying	Non-service
15t16	Food, beverages and tobacco	Non-service
17t18	Textiles and textile products	Non-service
19	Leather, leather products and footwear	Non-service
20	Wood and products of wood and cork	Non-service
21t22	Pulp, paper, paper products, printing and publishing	Non-service
23	Coke, refined petroleum and nuclear fuel	Non-service
24	Chemicals and chemical products	Non-service
25	Rubber and plastics	Non-service
26	Other non-metallic mineral products	Non-service
27t28	Basic metals and fabricated metal products	Non-service
29	Machinery nec	Non-service
30t33	Electrical and optical equipment	Non-service
34t35	Transport equipment	Non-service
36t37	Manufacturing nec, recycling	Non-service
E	Electricity, gas and water supply	Non-service
F	Construction	Non-Service
50	Sale, maintenance and repair of motor vehicles	Service
51	Wholesale trade and commission trade	Service
52	Retail trade, except motor vehicles and motorcycles	Service
H	Hotels and restaurants	Service
60	Inland transport	Service
61	Water transport	Service
62	Air transport	Service
63	Supporting and auxiliary transport activities	Service
64	Post and telecommunications	Service
J	Financial intermediation	Service
70	Real estate activities	Service
71t74	Renting of machinery and equipment and other business activities	Service
L	Public administration and defence, social security	Service
M	Education	Service
N	Health and social work	Service
O	Other community, social and personal services	Service

6. Unmeasured investment and the puzzling Japanese lost decades[*]

For the mid to late 1990s and early 2000s, the basic neoclassical growth theory predicts a steady Japanese economy, when in fact the Japanese economy was depressed. This study applies the new theory with intangible investment and non-neutral technology proposed by McGrattan and Prescott (2010) to the Japanese economy, and finds that the predictions derived from the new theory are much closer to the actual data. The improvement of this extension remains robust when tangible investment adjustment costs are added. This study is the first to apply the new theory to a country other than the US, and compared with existing literature on the lost decades of Japan, this study better explains the depression in labour hours by avoiding introducing a large, unjustified labour wedge or other exogenous inputs.

6.1 Introduction

The basic neoclassical growth theory accounts well for the fluctuation of the Japanese economy prior to the 1990s, provided that productivity and government purchase shocks are incorporated. During the 1990s and 2000s, however, the behaviour of the Japanese economy often deviates from this model, as indicated not only by the depression in labour hours but also most macroeconomic variables[1]. Although Hayashi

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[*] This chapter is also published in Crawford School Research Paper (No. 01/2017).

[1] See, for example, Figure 3 in Kobayashi and Inaba (2006). The basic real business cycle model explains the fluctuation of the Japanese economy well prior to the 1990s. From the 1990s, however, the deviation of the simulation results based on TFP shocks and government purchase shocks from the actual data keeps increasing over time.

and Prescott (2002) explain the pre-1995 counterfactual predictions by arguing that there was a policy change in the working hours limit, the deviations of the predictions from the actual data were persistent after 1995. Specifically, the model predicts a steady mid to late 1990s and early 2000s economy, when in fact it was depressed. For example, over the period of 1995 to 2007, Japanese nominal GDP fell from $5.33 to $4.36 trillion while the nominal wages at current USD fell around 10% according to statistics from the World Bank[2]. Accordingly, the 1990s and 2000s are called the lost decades or the lost 20 years of Japan. The existing literature argues that the decline in TFP is the main cause of the lost decades in Japan (Fukao and Kwon, 2006; Griffin and Odaki, 2009; Hayashi and Prescott, 2002), which is inconsistent with the counterfactual predictions generated by the neoclassical growth model when TFP shocks are incorporated.

Following McGrattan and Prescott (2010) and McGrattan and Prescott (2014), this study extends the base model by introducing intangible investment and non-neutral technology change with respect to the production of intangible investment goods and finds that, in the light of the new theory proposed by McGrattan and Prescott (2010) and McGrattan and Prescott (2014), the lost decades in Japan are much less puzzling. Most intangible investment is excluded from gross domestic output (GDP) because it is difficult to measure. Examples of intangible investment include research and development (R&D), advertising, organization capital, staff training, etc. These investments[3] are traditionally treated as expenditure and do not appear in the national

[2] The World Bank data (http://data.worldbank.org/country/japan).
[3] From 2016, Japan began to capitalize innovative property including R&D, mineral exploration and evaluation as well as software using SNA08. Although a part of intangible investment is captured by SNA08, there is still a large proportion of intangible investment that remains uncaptured due to

account. However, these investments are made for realizing future profits and are reflected in the valuation of a company when the company goes public or is sold (Asker et al., 2015; Eisfeldt and Papanikolaou, 2013; Hulten and Hao, 2008). The importance of intangible investment in economic activities has been widely confirmed in the literature (Arato and Yamada, 2012; Atkeson and Kehoe, 2005; Awano et al., 2010; Borgo et al., 2013; Chun and Nadiri, 2016; Clausen and Hirth, 2016; Corrado et al., 2013, 2009; Corrado and Hulten, 2010; Eisfeldt and Papanikolaou, 2013, 2014; Fukao et al., 2009; Gourio and Rudanko, 2014a, 2014b; Haskel and Wallis, 2013; Marrano et al., 2009; Miyagawa and Hisa, 2013; Tronconi and Marzetti, 2011; van Ark et al., 2009), and missing this critical element might cause problems for macroeconomic theories.

There is both macroeconomic and microeconomic evidence suggesting that the unmeasured investment was depressed during the lost decades. According to Fukao et al. (2009) and the intangible investment data they used, the growth rate of real intangible investment was low and sometimes negative during the lost decades. From 1985 to 1992, real intangible investment in the Japanese economy grew by 48% while it only grew respectively by 14% and 9.6% from 1992 to 1999 and from 1999 to 2006 in real terms[4]. If we look at the industrial level data, it is clear that the intangible investment was significantly low compared with previous periods. Taking Japan's semiconductor industry as an example, from 1985 to 1992, its intangible investment

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measurement issues. The national account data used in this study is obtained from Penn World Table 8.1 and does not include R&D, mineral exploration and evaluation, in order to separate most of the intangible investment from the output of goods and services.

[4] Data from JIP database 2011 (http://www.rieti.go.jp/en/database/JIP2011/).

quadrupled, while it decreased by 5% between 1999 and 2006[5]. Moreover, during the Asian Financial Crisis, Japanese output and working hours fell significantly while labour productivity rose or fell much less than the output and working hours[6], which is inconsistent with the predictions of current macro theories that assume business cycles are, at least partially, driven by shocks of total factor productivity. McGrattan and Prescott (2014) argue that the current business cycle theory is likely to miss the unmeasured intangible investment based on similar phenomena that took place in the US during the downturn of 2008–2009.

The counterfactual predictions of the base neoclassical growth model for the Japanese economy during the lost decades is consistent with a theory that distinguishes measured income and economic income. When economic income does not move with measured income, measured productivity may deviate from actual productivity and the predictions based on the measured productivity are likely to be inconsistent with the real data. To uncover what actually happened during Japan's lost decades, this study incorporates the intangible investment into the basic neoclassical growth model following McGrattan and Prescott (2010) and McGrattan and Prescott (2014). There are two activities in the economy: the production of final goods and services, and the production of intangible investment goods[7]. Following McGrattan and Prescott (2010) and McGrattan and Prescott (2014), this study assumes hours allocated to these two activities are measured

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[5] Data from JIP database 2011 (http://www.rieti.go.jp/en/database/JIP2011/).

[6] Data from Total Economy Database (https://www.conference-board.org/data/economydatabase/). In terms of labour productivity per hour, it rose both in 1998 and 1999. In terms of labour productivity per person, it fell slightly in 1998 and rose in 1999.

[7] The intangible investment in this study is different from that in Corrado et al. (2009) and the literature based on Corrado et al. (2009). The intangible investment in this study is derived from macroeconomic theory while that of Corrado et al. (2009) is derived from the available data.

accurately, and reported income is underestimated by the amount of intangible investments. Given the inaccurate nature of intangible investment measurement, this study uses the extended model to determine the path for the intangible investment following McGrattan and Prescott (2010) and show why including the missing intangible investment is important for understanding the lost decades of Japan.

This study allows the rates of technological change to differ across both the sector producing final goods and services and the sector producing intangible investment goods following McGrattan and Prescott (2010) and McGrattan and Prescott (2014)[8]. To generate working hours consistent with reality, one could have introduced large and variable shocks to leisure preference or labour market frictions, which is a common practice in business cycle research (McGrattan and Prescott, 2010). The advantage of the new theory proposed by McGrattan and Prescott (2010) and McGrattan and Prescott (2014) is that it can avoid introducing large changes of leisure preferences or labour market frictions that often cannot be justified by observations on tax rates, which makes this theory better satisfy the input justification criterion. That is, the exogenous input of this theory is more consistent with micro and macro evidence.

Another requirement for a successful theory is to satisfy the prediction criterion. That is, a theory must not produce counterfactual predictions, at least. A stronger requirement is to make correct predictions for data that were not used to calibrate parameters. Therefore, this study follows Prescott and McGrattan (2007) by calibrating the model

[8] For the rationale of this modelling choice, please see McGrattan and Prescott (2010) and McGrattan and Prescott (2014).

using the initial year data instead of data of the research period as well as using only TFP shocks and government wedge shocks because if all exogenous inputs are used, then a perfect match between data and theory will be obtained no matter what theory is used.

This study is the first to apply this new theory to an economy other than the US and therefore provides important evidence for the applicability of the new theory. To confirm the robustness of the extension proposed by McGrattan and Prescott (2010), an alternative neoclassical growth model with tangible investment adjustment costs is further applied. This study also provides a better explanation for the lost decades of the Japanese economy compared with previous literature. For example, Kobayashi and Inaba (2006) argue that labour market frictions play an important role in the lost decades of Japan but the increased frictions cannot be justified by observations on tax rates or structural changes. By applying the method proposed by McGrattan and Prescott (2010) and McGrattan and Prescott (2014) to the Japanese economy between 1995[9] and 2006[10], it is found that the prediction results of the new theory are much more consistent with the actual data compared with those of the base model, which indicates that this new theory is also applicable to Japan. The findings suggest that the standard productivity measures greatly underestimate the actual fall in labour

[9] Hayashi and Prescott (2002) have explained the pre-1995 deviations using the changed working hours limit. Moreover, the effective labour tax rate is an important element of the new theory proposed by McGrattan and Prescott (2010) and McGrattan and Prescott (2014) but the national account data needed in the calculation of the effective labour tax rate is unavailable for Japan before 1994. Therefore, 1995 is chosen as the initial year.

[10] During the Global Financial Crisis, both the base model and the model extended with intangible investment and non-neutral technology do not work well due to dramatic financial frictions, though the extended model works better. However, the prediction results of both models are consistent, which indicates that the movement of measured output and unmeasured investment is consistent in Japan during the GFC. Therefore, I choose 2006 as the terminal year.

productivity during most of the time in the Japanese lost decades.

This paper is organized as follows. The following section demonstrates the prediction results from the basic neoclassical theory. Section 3 provides the evidence of decreased intangible investment during the research period. Section 4 shows the extended theory and its predictions. Section 5 introduces the alternative model setting. Section 6 draws the conclusion.

6.2 Predictions of the basic theory without intangible investment

The starting point is the basic neoclassical growth model that is often used in the study of business cycles. The basic model used in this study is a simplified version of that used in McGrattan and Prescott (2010) by eliminating most of the tax rates except the labour income tax[11]. Therefore, it is closer to the model used in the business cycle accounting literature (Chari et al., 2007; Kersting, 2008; Kobayashi and Inaba, 2006). In the basic model, I treat TFP, labour income tax rate, population and the public consumption exogenously, which is consistent with McGrattan and Prescott (2010) and McGrattan and Prescott (2014).

In a standard one-sector neoclassical growth model, given the initial capital stock k_0, a representative household chooses consumption c, investment x and working hours h to maximize

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[11] Other tax rates or frictions except the labour income tax rate generally remain stable over the research period in Japan and therefore are already embodied in either the initial investment wedge that is normalized to 1 or the initial parameter settings. Therefore, it is reasonable to use the simplified version.

$$\mathrm{E}_0[\sum_{t=0}^{\infty}\beta^t U(c_t, h_t)N_t]$$

subject to

$$c_t + x_t = (1 - t_{wt})w_t h_t + r_t k_t + T_t$$

$$k_{t+1} = [(1-\delta)k_t + x_t]/(1+n)$$

The lowercase variables are written in per capita terms and $N_t = N_0(1+n)^t$ is the population in time t. r_t is the capital rent while w_t is the labour wage rate. Households discount their utility at the discount rate β, and the capital depreciation rate is δ. t_{wt} is the labour income tax, which is the main component of the labour wedge according to the theory of business cycle accounting.

The aggregate production function is labour augmented and in the form of Cobbs-Douglas, which is as follows:

$$\mathrm{Y}_t = (A_t H_t)^{1\text{-}ak} K_t{}^{ak}$$

Capital letters denote aggregate variables. A_t is TFP that varies over time, H_t is the total working hours and K_t is mainly the tangible capital stock[12]. K_t is calculated by applying the perpetual inventory method to investment in the national account. Firms rent capital and employ labour. ak is the capital income share in the production. If profits are maximized, then both the rental rate of capital and the wage rate of labour are respectively equal to the marginal product of each. The clearing condition of the goods and service market is $\mathrm{N}_t(c_t + x_t + g_t) = \mathrm{Y}_t$. g_t is the government purchase or the

[12] It includes software, however.

government wedge.

Following McGrattan and Prescott (2010), I first calibrate the model based on the data of the initial year, and then compute the model's equilibrium path assuming households have perfect foresight[13] of future changes in labour income tax rates, TFP, public consumption and populations. In Appendix A, I discuss the data sources of the variables and the parameterization of the model. The parameters used to compute the equilibrium path of this model are summarized in Table A1. The effective labour income tax rate, the public consumption, and the TFP are reported in Table A2. The process of computing the equilibrium path is described in detail in Appendix A. The tax rate change I consider in this study is the effective labour income tax rate t_{wt}, which is constructed using the method proposed by Mendoza et al. (1994). The method proposed by Mendoza et al. (1994) is also used in Prescott (2004) and McGrattan and Prescott (2010). The data for constructing effective the labour income tax rate is obtained from OECD national account and revenue statistics[14].

The utility function used in this study is standard in the business cycle literature, as follows:

$$U(c,l) = log\ c + \psi log(1-h)$$

ψ is the leisure preference parameter. Assume a technology progress rate γ, and the technical progress rate is derived from the average growth rate of GDP per working age

[13] The simulation process is based on the fully nonlinear approach instead of the log-linearization approach, to ensure the accuracy of the simulation. Therefore, perfect foresight is assumed.
[14] OECD statistics (https://stats.oecd.org).

person between 1995 and 2006, which is standard in the business cycle literature.

Therefore, we have the first order conditions as follows:

$$\frac{\psi\hat{c}_t}{1-h_t} = (1-t_{wt})\frac{(1-ak)\hat{y}_t}{h_t}$$

$$\mu_t = \hat{\beta}E_t\mu_{t+1}[(1-\delta) + \frac{ak\hat{y}_{t+1}}{\hat{k}_{t+1}}]$$

where $\hat{\beta} = \beta/(1+\gamma)$, $\mu = 1/\hat{c}$, E_t denotes expectation. The hat on a variable indicates that it has been detrended by $(1+\gamma)^t$. For example, $\hat{c}_t = c_t/(1+\gamma)^t$.

To close the model, I add the resource constraint and the motion of capital:

$$\hat{c}_t + \hat{x}_t + \hat{g}_t = \hat{y}_t$$

$$\hat{y}_t = (A_t\hat{h}_t)^{1-ak}\hat{k}_t^{\;ak}$$

$$\hat{k}_{t+1} = [(1-\delta)\hat{k}_t + \hat{x}_t]/[(1+n)(1+\gamma)]$$

The initial capital stock in 1995 is derived from the Penn World Table 8.1[15]. Following McGrattan and Prescott (2010), I choose the depreciation rate δ based on the capital stock and the investment of Japan in 1995. Then I choose the utility parameter ψ so that the model's consumption share, investment share and factor inputs share are consistent with the Japanese level in 1995 (see Appendix A and B for details). Then, I incorporate technology changes and government purchase changes into the model above and obtain the prediction results as follows:

[15] For the detailed introduction of Penn World Table 8.1, please see Feenstra et al. (2015).

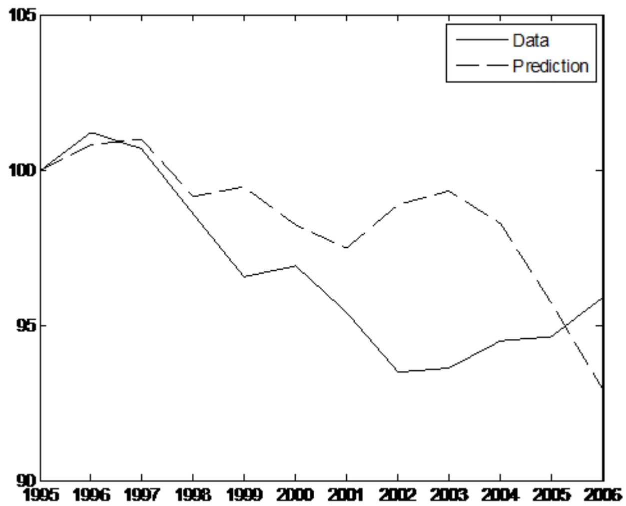

Figure 1 Japan and basic model per capita hours worked
(Annual, 1995=100, 1995–2006)

In Figure 1, I plot the model's predicted per capita working hours and the actual per capita working hours, indexed so that 1995 equals 100. The difference between the two series is noticeable. Actual per capita hours were depressed during the research period while the predicted per capita hours mostly remained steady between 1995 to 2006.

In Figure 2, I plot the model's predicted output along with the real GDP of Japan. Both series are adjusted according to the population growth and a technological progress rate of 1.015^t. Although the depression in output was not as large as the depression in hours, the model predicts that the economy should have boomed.

In Figure 3, I plot the model's predicted tangible investment along with the actual tangible investment of Japan. Obviously, significant deviations from the actual data are observed. A similar phenomenon happens in consumption, which is displayed in Figure 4.

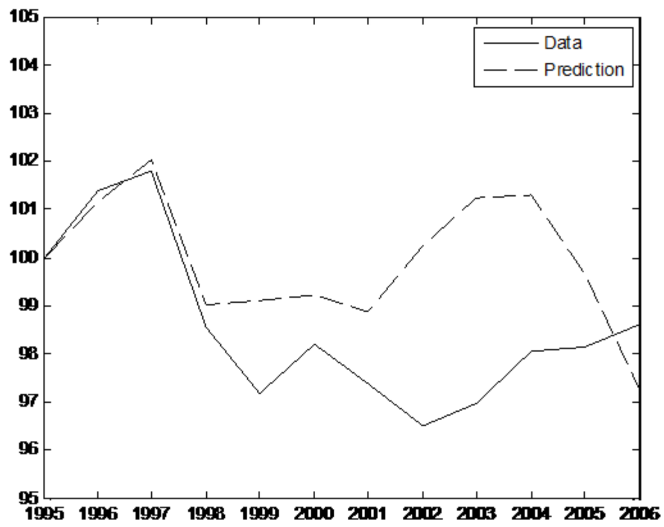

Figure 2 Japan and the basic model real GDP per capita
(Detrended by 1.015^t, annual, 1995=100, 1995–2006)

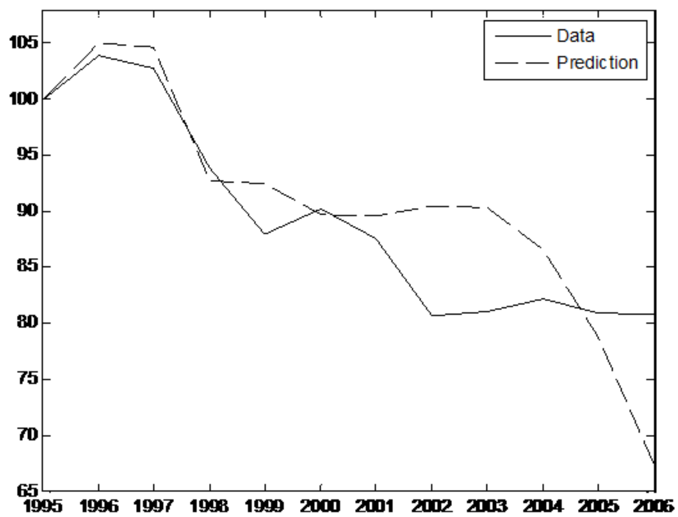

Figure 3 Japan and the basic model tangible investment per capita
(Detrended by 1.015^t, annual, 1995=100, 1995–2006)

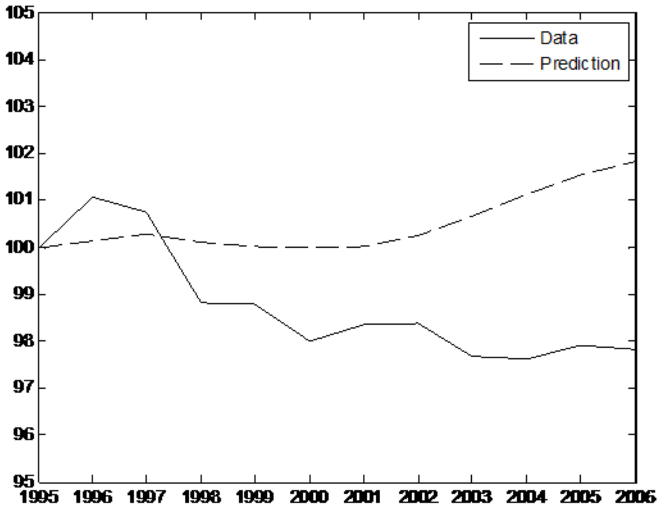

Figure 4 Japan and the basic model consumption per capita
(Detrended by 1.015^t, annual, 1995=100, 1995-2006)

6.3 Evidence of decreased intangible investment

I present evidence that suggests unmeasured intangible investment was low during most of the time between 1995 and 2006. If all incomes were included in national accounts, we would expect the growth rate of labour productivity per hour, labour hours and output to be low during a depression because if labour productivity per hour is high, firms employ more people and as a result the labour hours and output increase. An examination of Japan's national accounts reveals that the growth rate of labour productivity was high compared with the growth rate of output and working hours in many years between 1995 and 2006 according to Figure 5, suggesting that the labour productivity per hour might be overstated. Since intangible investments are expensed in the national account, the measurement of labour productivity is overstated to a significant extent when these investments decreased more than the output of goods and services or grew less than the output of goods and services. Specifically, during the lost decades, firms might have cut intangible investment and transferred the resources that had been used to produce intangible investment to the production of goods and services. As a result, measured labour productivity did not decrease as much as the actual labour productivity.

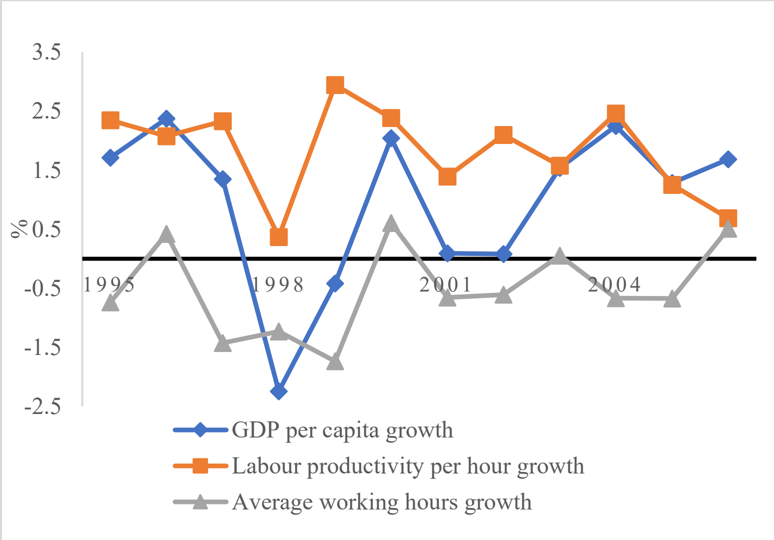

Figure 5 The growth of GDP per capita, labour productivity per hour and average working hours in Japan (Annually)
Source: Author's own construction; data from Total Economy Database (https://www.conference-board.org/data/economydatabase/).

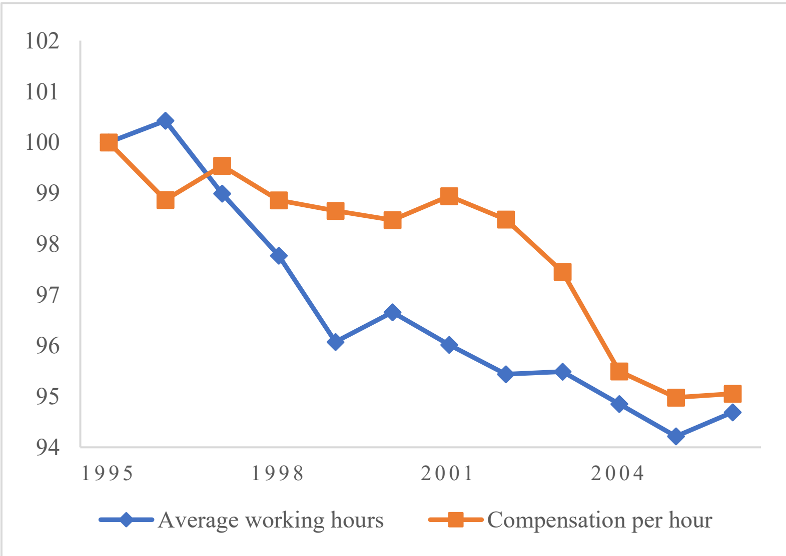

Figure 6 The average working hours and compensation per hour in Japan
(Compensation per hour detrended by 1.015^t, annual, 1995=100, 1995–2006)
Source: Author's own construction; data from Total Economy Database (https://www.conference-board.org/data/economydatabase/) and OECD national account statistics.

In Figure 6, I plot the average working hours and compensation per hour in Japan. The average working hours have been adjusted according to the population growth rate, and the compensation per hour is adjusted according to the price level provided by the Penn World Table 8.1 and technology growth rate. Please note that labour compensation per hour is another indicator of labour productivity. It is evident that the movements of average working hours and compensation per hour are inconsistent during the research period. In some years, the compensation per hour grew while the working hours per labour declined, which may indicate that the unmeasured investment was low in many years.

6.4 Predictions of the extended theory with intangible investment

According to McGrattan and Prescott (2010) and McGrattan and Prescott (2014), the technology used in producing final goods and services should be different from that used in producing intangible investment. Therefore, the extended theory should include not only intangible investment but also non-neutral technology. The household problem remains the same as that in section 2 except that there is an additional investment choice. I examine the extended model's predictions and show that these predictions conform with Japanese observations between 1995 and 2006.

Extensions

The aggregate production comprises two aggregation production relations:

$$y_t = (A_t^1 h_t^1)^{1-ak-ai} (k_{Tt}^1)^{ak} (k_{It})^{ai}$$

$$x_{It} = (A_t^2 h_t^2)^{1-ak-ai} (k_{Tt}^2)^{ak} (k_{It})^{ai}$$

Firms produce final goods and services using intangible capital k_I, tangible capital k_T^1

and labour h^1. Firms produce new intangible capital x_I, such as new brands, new products R&D, staff training, etc., using intangible capital k_I, tangible capital k_T^2 and labour h^2. It is difficult to acquire the parameters of the intangible investment production because of the lack of data. For simplicity, I assume the income shares of the three production factors are the same between the two activities following McGrattan and Prescott (2010). According to McGrattan and Prescott (2010), varying the parameters of the production function of intangible investment does not change the implications of the new theory.

Following McGrattan and Prescott (2010) and McGrattan and Prescott (2014), k_I is an input to both sectors. It is not split between them as is the case for tangible capital and labour because it can be used in different productions simultaneously. For example, a brand name is used both to sell final goods and services and to develop new brands; new knowledge from R&D is used by both producers and researchers. Given initial capital (k_{It}, k_{Tt}), the maximization problem of the household is

$$\mathrm{E}_0[\textstyle\sum_{t=0}^{\infty} \beta^t U(c_t, h_t) N_t],$$

subject to

$$c_t + x_{Tt} + q_t x_{It} = (1 - t_{wt}) w_t h_t + r_{Tt} k_t + r_{It} k_{It} + T_t.$$

$$k_{T,t+1} = \left[(1 - \delta_T) k_{T,t} + x_{Tt}\right] / (1 + n)$$

$$k_{I,t+1} = \left[(1 - \delta_I) k_{I,t} + x_{It}\right] / (1 + n)$$

As before, all lowercase variables are in per capita units and there is a growth of population at rate n. The relative price of intangible investment is q_t. The rental rate of intangible capital and tangible capital are respectively denoted by r_{It} and r_{Tt}. The transfer payment is denoted by T_t and is exogenous in the household's decision problem. Labour income is $w_t h_t$. The first order conditions are as follows:

$$\frac{\psi \hat{c}_t}{1-h_t} = (1-t_{wt})\frac{(1-ak-ai)\hat{y}_t}{h_t^1} \tag{1}$$

$$\mu_t = \hat{\beta} E_t \mu_{t+1}[(1-\delta_T) + \frac{ak\hat{y}_{t+1}}{\hat{k}_{t+1}}] \tag{2}$$

$$q_t \mu_t = \hat{\beta} E_t \mu_{t+1}[q_{t+1}(1-\delta_T) + \frac{ai(\hat{y}_{t+1}+q_{t+1}x_{It+1})}{\hat{k}_{t+1}}] \tag{3}$$

$$\frac{\hat{y}_t}{{h_t}^1} = \frac{q_t \hat{x}_{It}}{{h_t}^2} \tag{4}$$

$$\frac{\hat{y}_t}{{k_t}^1} = \frac{q_t \hat{x}_{It}}{{k_t}^2} \tag{5}$$

The hat on a variable indicates that it has been detrended by $(1+\gamma)^t$. To close the model, I again add the resource constraint and the capital motion:

$$\hat{c}_t + \hat{x}_t + \hat{g}_t = \hat{y}_t \tag{6}$$

$$\hat{y}_t = (\mathrm{A}_t^1 h_t^1)^{1-ak-ai}\left(\hat{k}_{Tt}^1\right)^{ak}(\hat{k}_{It})^{ai} \tag{7}$$

$$\hat{x}_{It} = (\mathrm{A}_t^2 h_t^2)^{1-ak-ai}\left(\hat{k}_{Tt}^2\right)^{ak}(\hat{k}_{It})^{ai} \tag{8}$$

$$\hat{k}_{T,t+1} = \left[(1-\delta_T)\hat{k}_{T,t} + \hat{x}_{Tt}\right]/[(1+n)(1+\gamma)] \tag{9}$$

$$\hat{k}_{I,t+1} = \left[(1-\delta_I)\hat{k}_{I,t} + \hat{x}_{It}\right]/[(1+n)(1+\gamma)] \tag{10}$$

Explaining the seemingly high wages

I showed earlier that there is a large deviation between predictions of the basic growth model and the Japanese data. The model predicts that the after tax real wage should remain steady between 1995 and 2006, leading to steady per capita hours and output. With the extended model, the measurement of the real wage is different and is consistent with the behaviour of output and hours.

The basic model measures the real wage as

$$\overline{w}_t = (1 - ak)\frac{y_t}{(h_t^1 + h_t^2)}$$

where ak is the capital share, y is the measured value added, and $h_t^1 + h_t^2$ is the total working hours. The problem with the measurement of labour productivity on the right side of the equation is that some hours are used to produce intangible investment. The hours used to produce y are h_t^1 and, therefore, the real wage measurement should be

$$w_t = (1 - ak - ai)\frac{y_t}{h_t^1}$$

where ai is the intangible capital share. $\frac{y_t}{h_t^1}$ is the labour productivity in producing final goods and services. The labour hours h_t^2 is used to produce intangible investment and is not part of the labour input in producing y. If the relative size of h_t^2 to $h_t^1 + h_t^2$ decreases, then $\overline{w}_t / w_t$ increases and the overstatement of true wages becomes more significant.

Moreover, the technology used in producing intangible investment and final goods and services should be different due to their different nature, and therefore should be influenced by different productivity shocks. This would imply a decrease in $\mathrm{A}_t^2/\mathrm{A}_t^1$. My hypothesis is that $\mathrm{A}_t^2/\mathrm{A}_t^1$ did decrease significantly, which led to a decrease in the relative hours allocated to the intangible investment production, namely $h_t^2/(h_t^1 + h_t^2)$.

Identifying the total factor productivities

The scale of the inputs and outputs of both production functions has to be determined in order to identify the total factor productivities. This requires splitting the hours and tangible capital between two production activities as well as determining the magnitude of intangible investment and capital.

To identify how much labour is allocated to the two production activities, I use the fact that the after tax real wage rate equals the marginal rate of substitution between leisure and consumption, following McGrattan and Prescott (2010). That is, using equation (1) in the first order conditions of the extended theory. Then, we have

$$h_t^1 = (1 - t_{wt}) \frac{(1 - ak - ai)\hat{y}_t}{\psi \hat{c}_t} (1 - h_t)$$

Please note that observations on consumption $\hat{c}_t$, total hours h_t, final goods and services $\hat{y}_t$ and the labour tax rate t_{wt} are available. Hours used in producing intangible investment is determined residually, which is $h_t^2 = h_t - h_t^1$.

The marginal products of labour in the two activities should be equal, which is the equation (4) in the first order conditions of the extended theory. Therefore, we have

$$q_t \hat{x}_{It} = \frac{{h_t}^1}{{h_t}^2} \hat{y}_t \tag{11}$$

which is the measurement of intangible investment. As per McGrattan and Prescott (2010), the derivation of intangible investment relies heavily on theory and observations on consumption, total working hours, final goods and services as well as the labour tax rate. This method has an advantage over direct measurement when some or all of the intangible investment is not or cannot be measured (accurately) due to data availability issues.

The allocation of tangible capital across the two activities is determined in a similar way to the allocation of labour hours. Specifically, the marginal products of tangible capital in the two activities should also be equal, which is equation (5) in the first conditions of the extended theory. Re-arrange this equation, we have

$$\hat{k}_t^{\,1} = \frac{\hat{y}_t \hat{k}_t}{(q_t \hat{x}_{It} + \hat{y}_t)}$$

Again, tangible capital allocated to the production of intangible investment is determined residually as

$$\hat{k}_t^{\,2} = \hat{k}_t - \hat{k}_t^{\,1}$$

If there is a sequence of the price q_t of the intangible investment, the already-computed sequence of outputs $q_t \hat{x}_{It}$ can be used to infer the sequence of the intangible investment, and with a given initial value for intangible capital stock $\hat{k}_{I,1995}$, I can use equation (10) to determine the sequence of intangible stocks. To achieve the above, I calculate the sequence of the intangible investment price q_t based on the intertemporal condition of intangible investment, which is equation (3) in the first order conditions of the extended theory:

$$q_t \mu_t = \hat{\beta} E_t \mu_{t+1} [q_{t+1}(1 - \delta_T) + \frac{ai(\hat{y}_{t+1} + q_{t+1} x_{It+1})}{\hat{k}_{It+1}}]$$

$q_{t+1} x_{It+1}$ is derived from equation (11), and $\hat{k}_{It+1}$ is derived from equation (10), which is the motion of intangible capital. Since we have the observations on output and consumption, q_{t+1} can be obtained given q_t. I normalize q_{1995}=1 following McGrattan and Prescott (2007) and then the sequence of q is obtained.

Finally, I obtain the varying TFP and government wedge according to equation (6), (9) and (10), and incorporate them along with the effective labour tax rate into the extended model to derive the prediction results in the following section.

Model predictions

Treating the TFP sequence and the government wedge sequence as the exogenous input, I calibrate the model based on the data in 1995, compute the equilibrium of all variables, and compare them with actual Japanese data. All of the parameters used in computing the equilibrium path are described in Appendix A and summarized in Table A1. Moreover, a sensitivity analysis is conducted in Appendix B.

In Figure 7, I display the results for per capita total working hours. Unlike the comparative results from the basic model (Figure 1), the predictions here are much more consistent with the actual data. The extended model predicts a slight fall in hours used in producing final goods and investment during most of the time between 1995 and 2006. However, because the fall in hours used in producing intangible investment is much more than those used in producing final goods and investment, the model predicts a significant depression in per capital total working hours.

In Figure 8, unsurprisingly, the modelled per capita output and the actual per capita output are close. In Figure 9, the predicted per capita tangible investment is almost the same as the actual data. In Figure 10, the predicted per capita consumption also generally captures the trend of the actual data.

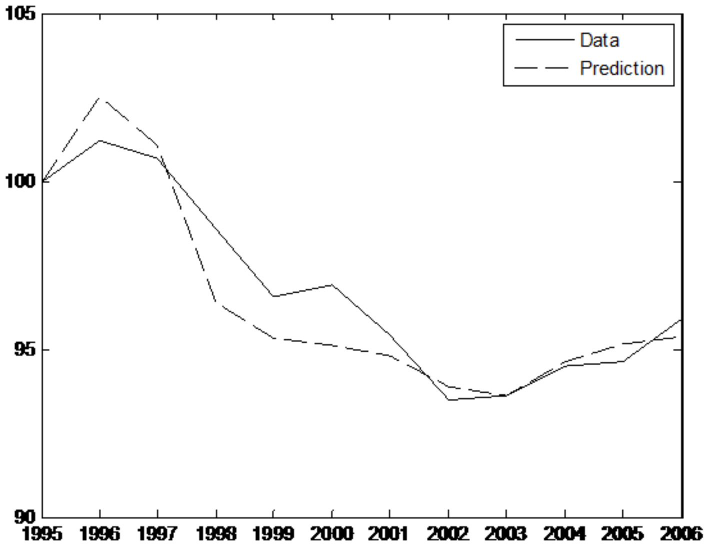

Figure 7. Extended model per capita total hours worked in Japan
(Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

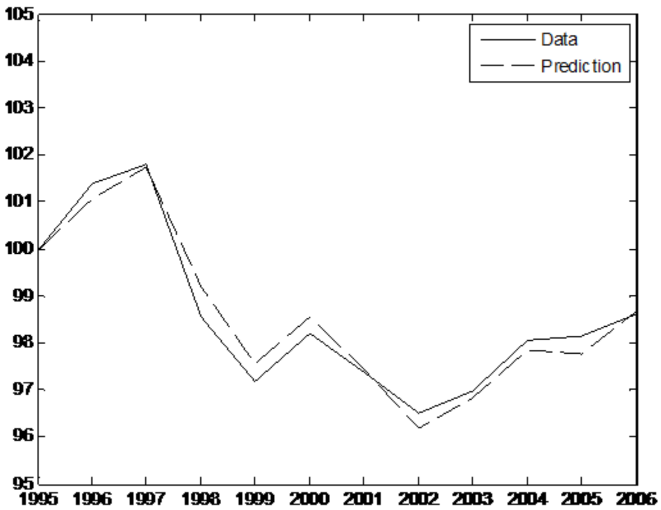

Figure 8. Extended model per capita real GDP in Japan
(Annual, series detrended by 1.015^t, 1995=100, 1995–2006)

Source: Author's own calculation.

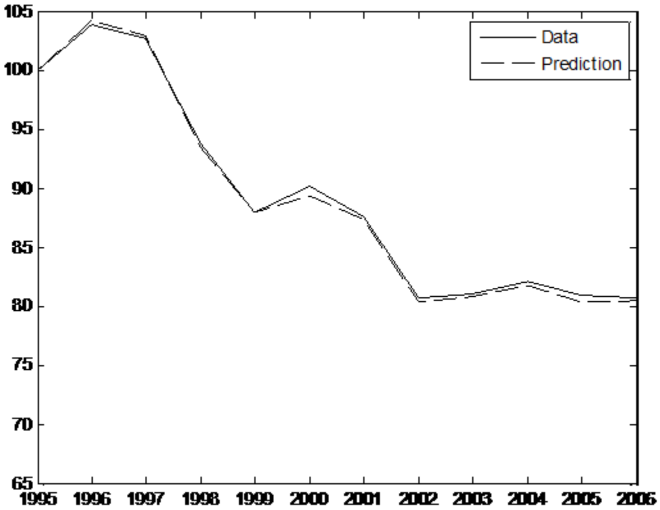

Figure 9. Extended model per capita tangible investment in Japan
(Annual, series detrended by 1.015^t, 1995=100, 1995–2006)
Source: Author's own calculation.

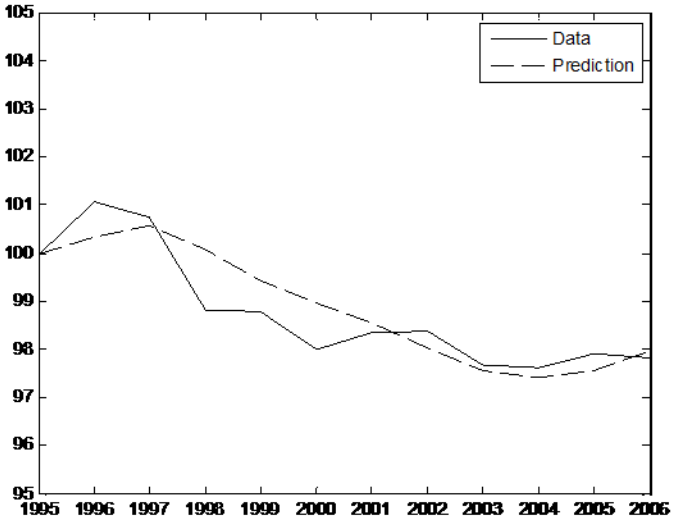

Figure 10. Extended model per capita consumption in Japan
(Annual, series detrended by 1.015^t, 1995=100, 1995–2006)
Source: Author's own calculation.

What does all this mean for Japanese labour productivity? If some output is unmeasured relative to input, then the change in productivity is biased when the unmeasured output does not move together with the measured output. The extended model's predictions for macro variables with or without intangible investment demonstrate how distorted the standard data and basic model are for assessing the lost decades of Japan.

In Figure 11, I compare two series of output per hour. One is output per hour without intangible investment included. The other is output per hour with intangible investment included. Obviously, with intangible investment incorporated, the puzzling labour productivity growth during the Asian Financial Crisis is no longer puzzling: labour productivity actually declined. Moreover, it is clear that the deviation of measured labour productivity and the actual labour productivity is significant. During the lost decades, the labour productivity of Japan was actually depressed, rather than booming.

In Figure 12, I compare the extended model's two measurements of total investment: one without intangible investment and the other with intangible investment. The two series of predictions are quite different, which indicates that the measured investment dramatically underestimates the actual decline in investment.

In summary, the results above show that standard accounting measurements and predictions of the standard model without intangible investment do not accurately reflect what was going on in Japan between 1995 and 2006. Therefore, the extended model is needed when conducting aggregate analyses.

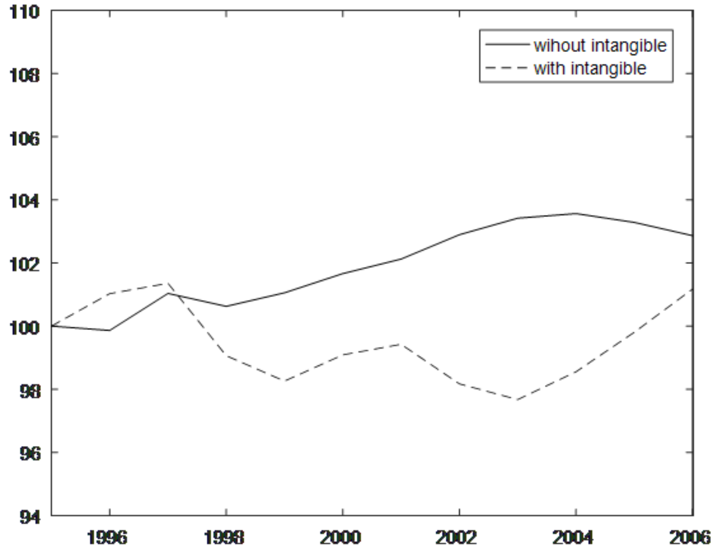

Figure 11. Labour productivity in Japan
(Annual, series detrended by 1.015^t, 1995=100, 1995–2006)
Source: Author's own calculation.

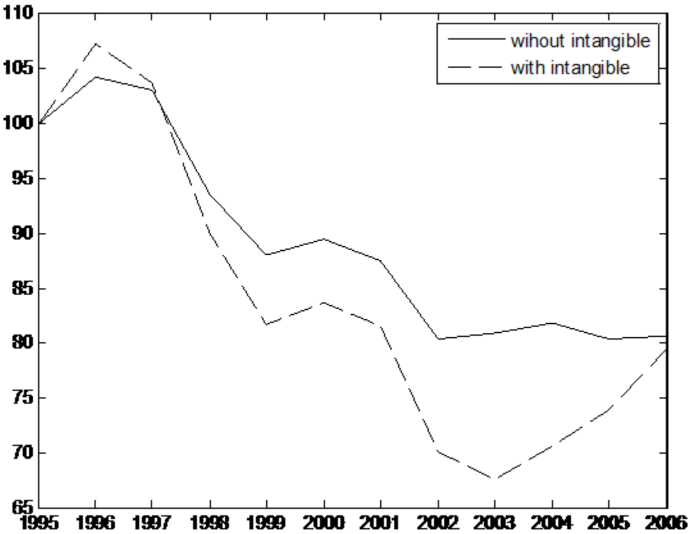

Figure 12. Extended model per capita investment in Japan
(Annual, series detrended by 1.015^t, 1995=100, 1995–2006)
Source: Author's own calculation.

6.5 Results with alternative model settings

In this section I test the robustness of the extension developed by McGrattan and Prescott (2010) with an alternative model with tangible investment adjustment costs. Christiano and Davis (2006) indicate that introducing tangible investment adjustment costs can affect the prediction results of neoclassical growth models. In this section, I modify the capital accumulation equations in both the basic model and the extended model to incorporate quadratic tangible investment adjustment costs.

In both the basic model and the extended model, the law of the motion of tangible capital turns into

$$\hat{k}_{t+1} = \left[(1-\delta)\hat{k}_t + \hat{x}_t - \Phi(\frac{\hat{x}_t}{\hat{k}_t})\hat{k}_t\right]/(1+n)$$

where

$$\Phi\left(\frac{\hat{x}_t}{\hat{k}_t}\right) = \frac{\phi}{2}(\frac{\hat{x}_t}{\hat{k}_t} - \lambda_T)^2$$

The constant λ_T of tangible capital is set at $\lambda_T = na - (1-\delta)$ so that the adjustment cost is equal to zero at steady state. The parameter ϕ is calibrated to match the marginal Tobin's Q to one:

$$\frac{\mathrm{dlog}q_T}{\mathrm{dlog}(\frac{\hat{x}}{\hat{k}})} = 1$$

where q_T is the effective price of tangible investment relative to consumption:

$$q_T = \frac{1}{1-\Phi'}$$

This leads to $\phi = \frac{\hat{k}}{\hat{x}}$.

The simulation results are similar to the original models: the basic alternative model fails to generate satisfying predictions and the extended alternative model improves the predictions significantly. Therefore, the extension proposed by McGrattan and Prescott (2010) is robust. The value of the additional parameter λ_T as well as the simulation results are demonstrated in Appendix C.

6.6 Conclusion

The basic neoclassical growth model accounts well for the Japanese economy prior to the 1990s, provided that variations in population growth, depreciation rates, total factor productivity (TFP) and government purchase are incorporated. The behaviour of the Japanese economy during the 1990s and 2000s, however, is often significantly inconsistent with the model predictions, which is also inconsistent with the argument in the literature that the decline in TFP is the main cause of the lost decades in Japan (Fukao and Kwon, 2006; Griffin and Odaki, 2009; Hayashi and Prescott, 2002).

Following McGrattan and Prescott (2010) and McGrattan and Prescott (2014), I find that the unmeasured intangible investment as well as the non-neutral technological change in intangible investment production led to the puzzling behaviour of the Japanese economy between 1995 and 2006. This change resulted in a depression in intangible investment, which is not reflected in the measured output. After applying the new theory, the puzzling lost decades in Japan become less puzzling.

This study is the first to apply this new theory to a country other than the US and finds that the new theory works well in Japan, even using a simpler version. Significant improvements in predictions are seen compared with the standard neoclassical model. The results remain robust when tangible investment adjustment costs are added. It also provides important evidence of the applicability of this new theory to other economies and strengthens the argument of McGrattan and Prescott (2010) that the new theory with intangible investment should be used in aggregate analyses.

6.7 Appendix A Data and parameters

The main sources of data in this study are the Penn World Table 8.1, OECD revenue and national accounts statistics, and the World Bank DataBank. The variables from the Penn World Table 8.1 that this study has used include total labour hours, real GDP, consumption share, investment share, government and net export share, labour compensation share; the variables from OECD revenue and national accounts statistics are used to calculate the effective labour income tax based on the method proposed by Mendoza (1994); the working age population (age 15–64) data is obtained from the World Bank DataBank. The calibration process used in this study follows McGrattan and Prescott (2007) and are demonstrated in Table A1. The exogenous inputs for simulation of the standard model and the extended model are respectively demonstrated in Table A2 and Table A3.

Table A1 Model parameters

Parameter	Expression	Value
Common parameters		
Growth in population	n	-0.003
Growth in technology	γ	0.015
Discount factor	β	0.98
Standard model, no intangible investment		
Utility parameter	ψ	4.44
Depreciation rate	δ	0.07
Capital share	ak	0.35
Extended model, with intangible investment		
Utility parameters	ψ	3.43
Tangible depreciation rate	δ_T	0.07
Intangible depreciation rate[16]	δ_I	0
Tangible capital share	ak	0.3276
Intangible capital share	ai	0.2064

Source: Author's own calculation.

[16] The depreciation rate of intangible capital follows McGrattan and Prescott (2010). However, I will conduct sensitivity analysis in Appendix B to show that the choice of the depreciation rate does not affect the results much.

Growth in population is derived from the working age population data; growth in technology is obtained from the average growth rate in value added per unit of labour; the discount factor follows McGrattan and Prescott (2010).

Parameters calculation and exogenous inputs for the standard model

Calibration is based on level data in 1995 instead of the average data and the following equations:

$$\delta = \frac{\hat{x}}{\hat{k}} + 1 - (1+n)(1+\gamma)$$

$$r = \frac{[1-\beta(1-\delta)]}{\beta}$$

$$\mathrm{ak} = \frac{r\hat{k}}{\hat{y}}$$

$$\psi = \frac{(1-t_{w,1995})(1-ak)(1-h)\hat{y}}{\hat{c}h}$$

$$\mathrm{z} = (\frac{\hat{k}}{\hat{y}})^{ak/(ak-1)}\frac{\hat{y}}{h}$$

z is the initial technology level; other notations are the same as those in the text. The exogenous inputs include the TFP, effective labour income tax and the government wedge, which are listed in Table A2.

Table A2 Exogenous inputs for the standard model

Year	Labour income tax	Government wedge	Technology parameter
	t_w	$\hat{g}$	A
1995	0.226005	0.148440931	3.19515
1996	0.226332	0.145587261	3.225424
1997	0.230106	0.154571707	3.255914
1998	0.225499	0.157813769	3.161069
1999	0.224183	0.160119394	3.167338
2000	0.236472	0.168758844	3.222646
2001	0.240673	0.165521832	3.24456
2002	0.236517	0.175462343	3.281042
2003	0.236543	0.183147381	3.325961
2004	0.243221	0.191610003	3.376623
2005	0.251445	0.19400152	3.396088
2006	0.257525	0.19977311	3.39723

Source: Author's own calculation.

Parameters calculation and exogenous inputs for the extended model

Again, calibration is based on level data in 1995 and the following equations:

$$r_T = \frac{[1-\beta(1-\delta_T)]}{\beta}$$

$$r_I = \frac{q[1-\beta(1-\delta_I)]}{\beta}$$

$$\hat{k}_I = \frac{\hat{y} - r_T\hat{k}_T - 1995\ labour\ compensation}{r_I - q[(1+\gamma)(1+n) - 1 + \delta_I]}$$

$$\hat{x}_I = ((1+\gamma)(1+n) - 1 + \delta_I)\hat{k}_I$$

$$ak = \frac{r_T\hat{k}_T}{\hat{y} + q\hat{x}_I}$$

$$ai = \frac{r_I\hat{k}_I}{\hat{y} + q\hat{x}_I}$$

$$z_1 = \left(\frac{\hat{y}}{{h_1}^{1-ak-ai}\hat{k}_T^{1\,ak}\hat{k}_I^{\,ai}}\right)^{\frac{1}{1-ak-ai}}$$

$$z_2 = \left(\frac{\hat{x}_I}{{h_2}^{1-ak-ai}\hat{k}_T^{2\,ak}\hat{k}_I^{\,ai}}\right)^{\frac{1}{1-ak-ai}}$$

z_1 and z_2 are respectively the initial production technology of final goods and services and intangible investment. The exogenous inputs include TFP for final goods and services and intangible investment, effective labour income tax and the government wedge.

Table A3 Exogenous inputs for the extended model

Year	Labour income tax	Government wedge	Technology parameter	
	t_w	$\hat{g}$	A_1	A_2
1995	0.226005	0.148440931	1.331588	0.421171
1996	0.226332	0.145587261	1.381845	0.457688
1997	0.230106	0.154571707	1.376854	0.437985
1998	0.225499	0.157813769	1.269788	0.369422
1999	0.224183	0.160119394	1.237311	0.320089
2000	0.236472	0.168758844	1.276741	0.343663
2001	0.240673	0.165521832	1.280091	0.336908
2002	0.236517	0.175462343	1.247973	0.249418
2003	0.236543	0.183147381	1.254313	0.200235
2004	0.243221	0.191610003	1.30684	0.251584
2005	0.251445	0.19400152	1.357024	0.328368
2006	0.257525	0.19977311	1.409351	0.408921

Source: Author's own calculation.

6.8 Appendix B Varying the depreciation rate of intangible capital

The depreciation rate of intangible capital is chosen to be 0 following McGrattan and Prescott (2010). In the following I will vary the depreciation to show that the results remain robust given different depreciation rates of intangible capital.

$\delta_I = 0.1$,

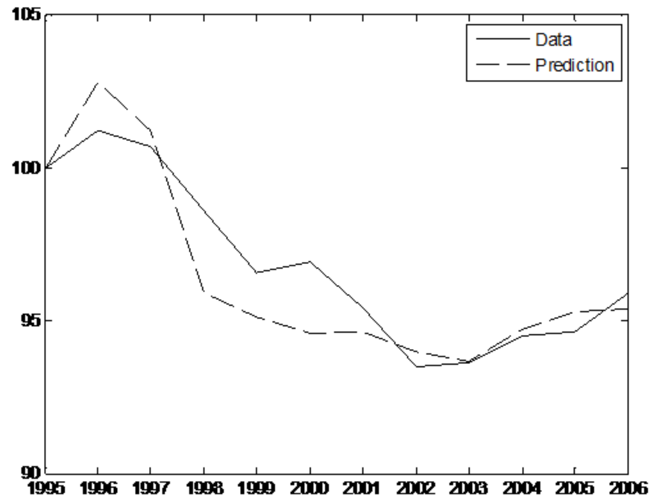

Figure B1 Extended model per capita total hours worked in Japan with $\delta_I = 0.1$ (Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

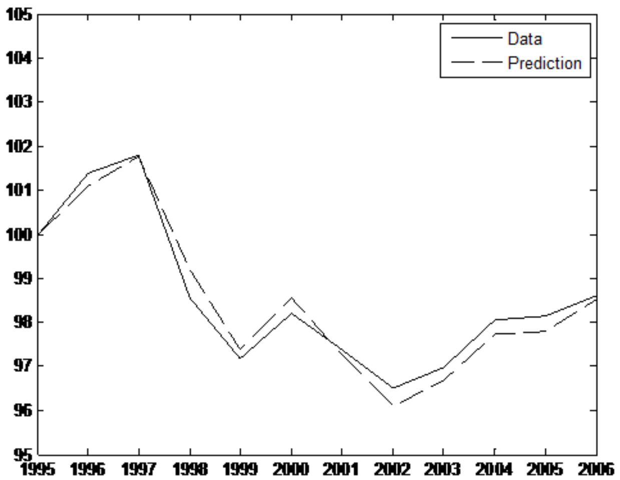

Figure B2 Extended model per capita real GDP in Japan with $\delta_I = 0.1$ (Annual, series detrended by 1.015^t, 1995=100, 1995–2006)

Source: Author's own calculation.

$\delta_I = 0.2$,

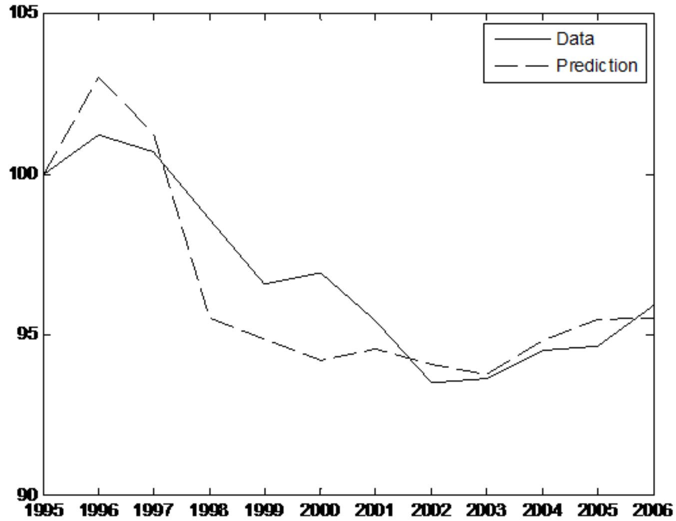

Figure B3 Extended model per capita total hours worked in Japan with $\delta_I = 0.2$ (Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

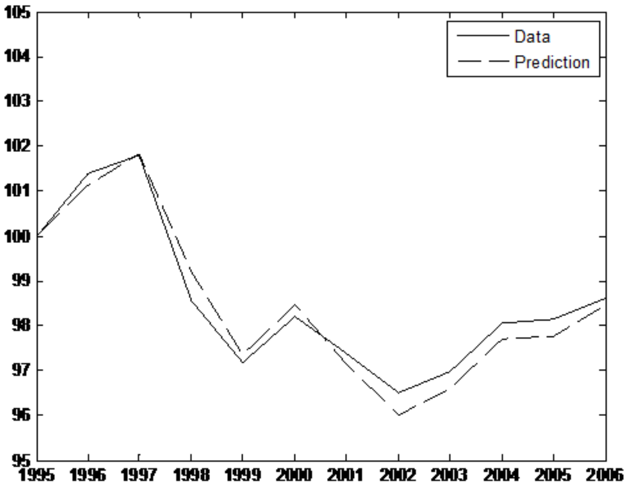

Figure B4 Extended model per capita real GDP in Japan with $\delta_I = 0.2$ (Annual, series detrended by 1.015^t, 1995=100, 1995–2006)

Source: Author's own calculation.

6.9 Appendix C Simulation results of models with tangible capital adjustment costs

According to the calibration method of λ_T in section 5, the value of λ_T is 0.0821.

Simulation results of the alternative models are demonstrated as follows:

The basic alternative model

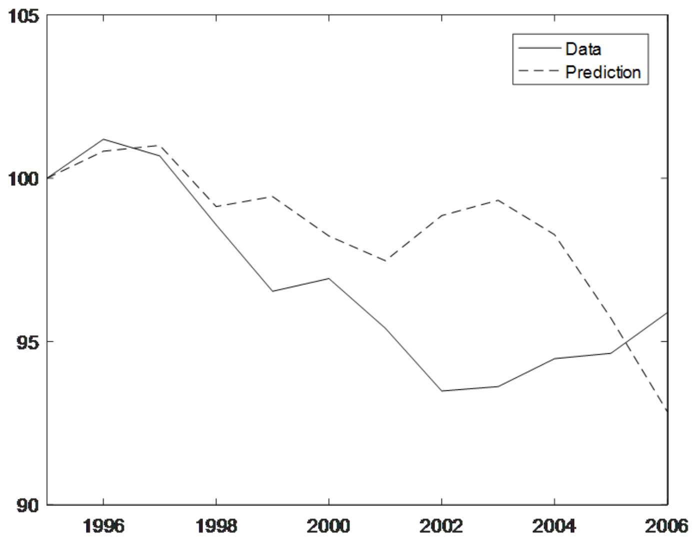

Figure C1 Basic alternative model per capita total hours worked in Japan (Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

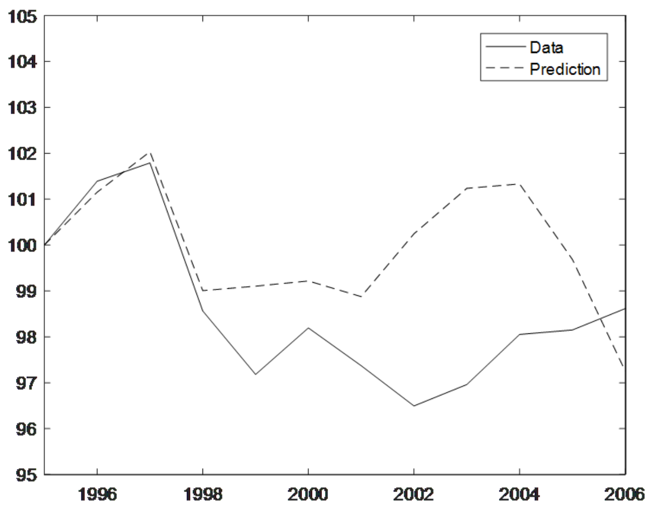

Figure C2 Basic alternative model per capita real GDP in Japan (Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

The extended alternative models

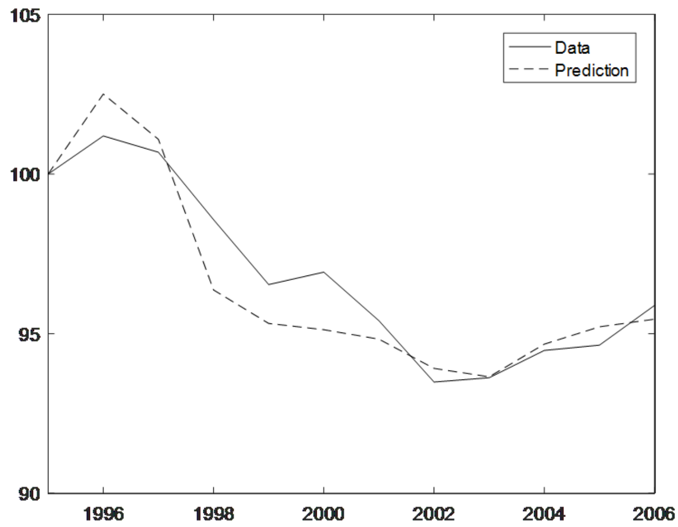

Figure C3 Extended alternative model per capita total hours worked in Japan (Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

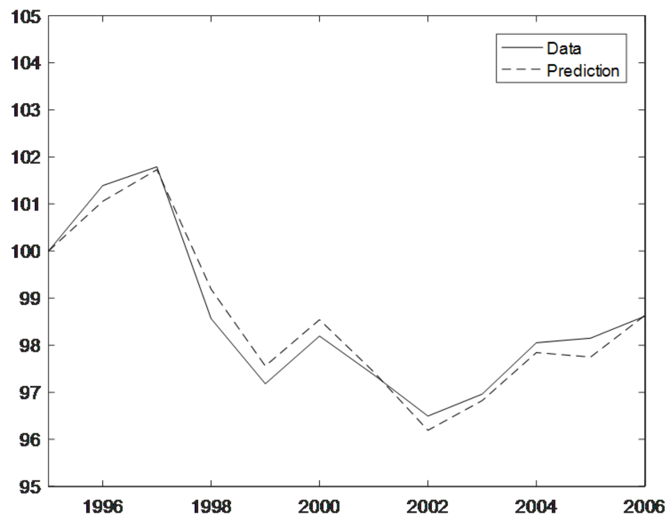

Figure C4 Extended alternative model per capita real GDP in Japan (Annual, 1995=100, 1995–2006)

Source: Author's own calculation.

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Conclusion

This thesis contributes to the literature on intangible capital and economic development by addressing the following questions which are dealt within each chapter of the thesis: What is the role of intangible capital in China's sectoral economic growth? What are the firm-level determinants of intangible investment in China? How does the effect of organization capital on firm performance vary between SOEs and non-SOEs in China? How does the role of intangible capital in sectoral energy intensity reduction differ across economies and sectors? How does the output elasticity and productivity spillover effect of intangible capital change between economies and sectors? What is the role of unmeasured intangible investment in explaining the Japanese real business cycles during the lost decades?

Chapter 1 confirms the important role of intangible capital in sectoral economic growth in China, and the significant contributions of intangible capital to economic growth remain robust across various forms of sensitivity analysis including bootstrap, IV-GMM, the Levinsohn and Petrin (2003) approach and changes in the depreciation rate. The relative importance of different categories of intangible capital in different industries has also been revealed: the role of R&D is important across all non-service industries while the role of economic competency is paramount across all non-agriculture industries. The usage of intangible capital in production in China, however, remains relatively small compared with that in advanced economies, which is consistent with China's role at the assembly end of global value chains and the fact that the investment in design / intellectual property / brands remains the preserve of more developed economies. Despite its relatively low intangible capital stock, China is catching up and there is every reason to believe that rapid growth in intangible capital will become an increasingly important driver of China's economic growth.

Chapter 2 reveals that more human capital, larger firm size and better institutional quality increase the propensity and the amount of intangible investment, and fiercer market competition generally decreases both the propensity and the amount to invest in intangibles. Specifically, firms facing an oligopoly market are more likely to invest in intangibles while firms facing a competitive market are less likely to invest in intangibles. The only exception is organization investment, where an inverted U-shape relationship with market competition is identified. Evidence on the propensity is more statistically robust than that on quantities. One interesting finding is that higher human capital is associated with a lower propensity for outsourced R&D, which is consistent with the fact that higher human capital can lower the costs of producing intangible investment. Another interesting discovery is that better institutional quality is associated with lower organization investment. A possible reason for this is that institutional quality is associated with the baseline organization capital and further investment is unlikely to improve productivity much if the baseline capital is high. Having explored the determinants of investment in intangibles, this chapter continues to examine the positive impacts of various intangible investment and ICT investment on the productivity of Chinese firms, which are all found to be significantly associated with the increase in productivity. Finally, policy implications on promoting intangible investment are derived from the empirical evidence of this chapter.

Chapter 3 finds that organization capital does play an important role in production in Chinese listed firms based on consistent evidence from OLS, fixed effects and the Levinsohn-Petrin (2003) models. Service is likely to rely more on organization capital than non-service. A simple theoretical model is built to explain the low employee turnover and less efficient organization capital in SOEs. It is found that due to the life-long job security, SOEs invest more in organization capital because of low employee turnover but their organization capital has lower efficiency due to the overpayment to their employees. Empirical result confirms the higher organization investment and the lower effect of organization capital in improving financial performance in SOEs. The findings of this chapter provide strong support for the continuing reform and privatisation in SOEs.

Chapter 4 compares the role of intangible capital in reducing sectoral energy intensity across economies and sectors and finds: 1) brand equity and organization capital improve sectoral energy intensity more than R&D; 2) intangible capital in low and middle income economies has a larger reduction effect on sectoral energy intensity than in high income economies; 3) sectors with high intangible capital ratio in the service group and equipment manufacturing sectors in the non-service group tend to enjoy larger effects from intangible capital on sectoral energy intensity reduction; 4) income level generally decreases the effect of intangible capital in reducing sectoral energy intensity but a moderate inverted U-shape relationship between income level and the effect of intangible capital in reducing sectoral energy intensity is identified in aggregate intangible capital as well as some disaggregated intangible capital including brand equity and organization capital. The findings of this chapter provide possible policy directions on reducing energy intensity through promoting intangible investment.

Chapter 5 discusses the effect of intangible capital on sectoral economic growth and productivity spillover based on a cross-country dataset derived from the WIOD database. It is found that intangible capital significantly contributes to both sectoral economic growth and productivity spillover. Both the output elasticity and productivity spillover of intangible capital demonstrate an inverted U-shape relationship with income level. Heterogeneity in the productivity spillover of intangible capital is also significant: it is found that the spillover effect is generally larger in service sectors than non-service sectors. The findings of this chapter partially answer the questions on the heterogeneous roles of intangible capital across sectors and economies, which might provide useful information for explaining the relationship between income inequality and economic growth. Policy makers might also find the information helpful by better understanding the changing roles of intangible capital in determining productivity spillover and then economic growth.

Chapter 6 demonstrates how the extended neoclassical growth model, incorporating unmeasured intangible investment and non-neutral technology, better explains the economic fluctuations in Japan during the lost decades. It is found that the unmeasured investment declined more than the measured output during the research period, which results in underestimation of the productivity decline and then the significant deviation from the predicted output to the actual data, using the base neoclassical growth model.

When unmeasured intangible investment is accounted for through the extension, the simulation results from the neoclassical growth model improve significantly and are close to the actual data. This chapter strengthens the important role of intangible investment in explaining real business cycles, and indicates the necessity to monitor intangible investment.

In conclusion, intangible capital plays a key role in economic growth and energy intensity as well as real business cycles. The heterogeneity in the role of intangible capital is also revealed, through economy and sector-specific parameters generated. It is also found that intangible investment can be increased by boosting human capital and institutional quality, and that monitoring intangible investment might improve the understanding of business cycles.

List of abbreviations

CFOA Operation cash flow of asset
CI Computerized information (a category of intangible capital)
DMR Difference in the marginal return between intangible capital and tangible capital
EC Economic competency (a category of intangible capital)
FE fixed effects model
ICT information and communication technology
JIP Database Japan Industry Productivity Database
LP Levinsohn and Petrin (2003)
R&D/RD Innovative property (research & development), which is also a category of intangible capital
RE Random effects model
ROA Return of asset
TFP Total factor productivity
S&GA Selling & General Administration
SNA08 System of National Account 2008
SOE State own enterprise
WIOD World Input Output Table

List of variables

Chapter 1

Variables	Source
Depreciation by industry	China Input-Output Tables 1997, 2002, 2007 and 2012, Bureau of Statistics of China
Total wages by industry	
Value added by industry	
Computer services and software intermediate by industry	
Research industry intermediate by industry	
Culture, arts, radio, movie and television industry intermediate by industry	
Business service industry intermediate by industry	
Education industry intermediate by industry	
Average wages by industry	Labour Statistics Yearbook of China
GDP deflator	The World Bank

Chapter 2

Variables	Source
R&D (Overall)	China Enterprise Survey 2012, the World Bank
R&D (Internal)	
R&D (Outsourced)	
Organization investment	
Software investment (dummy)	
Number of full-time employees	
Fixed asset	
IT equipment investment	
Average education years of permanent workers	
Export (dummy)	
Number of competitors	
NERI Index of Marketization	National Economic Research Institute (NERI) (Fan et al., 2011)

Chapter 3

Variables	Source
Annual sales	China Stock Market and Accounting Research Database (CSMAR)
Book assets	
Number of employees	
Selling, general and administrative expense	
Consumer Price Index (CPI)	
Proportion of state-owned shares	
Return of asset	
Total debt	
Total assets	

Chapter 4

Variables	Source
Gross fixed investment in computerized information	The Word Input-Output Table Database
Computer and related services intermediate	
Research and development services intermediate	
Other business activities intermediate	
Education services intermediate	
Value added	
Total intermediate	
Energy use	
Physical capital stock	
GDP per capita	the Penn World Table 8.1
GDP	

Chapter 5

Variables	Source
Gross fixed investment in computerized information	The Word Input-Output Table Database
Computer and related services intermediate	
Research and development services intermediate	
Other business activities intermediate	
Education services intermediate	
Value added	
Total intermediate	
Physical capital stock	
Number of employees	
GDP per capita	the Penn World Table 8.1
GDP	

Chapter 6

Variables	Source
Working age population growth	The Penn World Table 8.1
GDP	
Investment	
Capital stock	
Consumption	
GDP per capita	
Labour compensation	
Working hours	Total Economy Database
Labour productivity growth per hour	